

**The Neuroscience of Creative Perception:
From Visual Ambiguity to Neuroacoustics**

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ABSTRACT

The neuroscience of creative perception: From visual ambiguity to neuroacoustics

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This thesis advances the understanding of creativity by exploring its connection with sensory perception, particularly through divergent perception, a concept that extends beyond traditional divergent thinking approaches. It posits that creative ideas emerge not only from how we generate thoughts but fundamentally from how we perceive our environment, emphasizing the role of sensory ambiguity in the creative process. By integrating cognitive neuroscience with music theory, this work examines the relationship between sensory ambiguity and creative perception. Using magnetoencephalography (MEG), it investigates the neural underpinnings of divergent perception and its interaction with stimulus properties and individual creativity levels through a series of theoretical work and experimental studies (Chapters 1 to 3). These studies reveal that the brain's processing of ambiguous stimuli and its spontaneous activity are influenced by the individual's level of creativity, particularly when exposed to scale-free visual stimuli. Transitioning from visual to auditory perception, the thesis introduces a musically-inspired model of brain dynamics, emphasizing the creative potential of biosignals and their inherent harmonic complexity for musical exploration (Chapters 4 and 5). This includes the development of a Python toolbox for harmonic analysis of biosignals, designed to facilitate artistic and scientific exploration of the latent harmonies in living systems. Through this interdisciplinary approach, the thesis underscores the significance of divergent perception in creativity and offers new tools and models for investigating the complex interplay between sensory ambiguity, perception, and creative output.

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THE NEUROSCIENCE OF CREATIVE PERCEPTION

From visual ambiguity to neuroacoustics

“Physical matter is music solidified.”

Pythagoras

Introduction

It always seemed to me that in moments of pure inspiration, knowledge was transcended, somehow bypassing the traditional modes of cognition. Creative expression can be considered one of the most complex manifestations of consciousness, being one of those states that empiricism takes time to shed light on. Indeed, the current renewal of interest in this realm of research can be interpreted primarily as the result of our technological advances, but also as a criticism of previously established models. Despite significant advancements, a crucial gap persists in our understanding of the relationship between creativity and perception of ambiguous stimuli. Traditional models have predominantly focused on cognitive aspects of creativity, often overlooking the intricate ways in which sensory perceptions contribute to creative processes. This research proposes a novel framework that integrates divergent perception—a perceptual counterpart to divergent thinking—into the study of creativity. Divergent perception, as defined here, refers to the capacity to discern multiple perceptual interpretations of sensory stimuli.

This investigation will employ cognitive neuroscience methods and innovative research-creation techniques, particularly focusing on the sonification of biosignals as a means of exploring sensory ambiguity. This thesis blends various perspectives and methodologies, drawing from neurophenomenology, gestalt theory, nonlinear dynamics, embodied aesthetics, computational models of harmonicity, and brain-computer interface design. The core objective is to draw parallels between creativity and perceptual ambiguity, with a specific emphasis on how creative expression can arise from ambiguous perceptions.

The first facet of this thesis (chapters 1, 2 and 3) proposes a comprehensive model linking creativity with the perception of ambiguous stimuli, and revolves around four pivotal research objectives:

- Developing a theoretical framework for divergent perception and suggesting mechanisms that link altered perceptual experiences with creative processes.
- Investigating pareidolia — the perception of distinct objects within ambiguous stimuli — as an indicator of creativity.
- Exploring how the complexity of stimuli, such as fractal dimension, affects pareidolia.
- Identifying electrophysiological markers associated with pareidolic states and their modulation by individual creativity levels.

The thesis is philosophically anchored in the notion that subjectivity and phenomenology are emergent properties of biological systems interacting with their environments (Petitot et al., 2000; F. J. Varela et al., 2017). In the philosophy of perception, phenomenology and gestalt theory provide a framework for understanding perception as an inherently creative act. Pareidolia, in this context, serves as a prime example of the creative interplay between subjective experience and the objective world. To systematically manipulate pareidolia in laboratory settings, I employed advanced neuroimaging techniques (magnetoencephalography; MEG) to investigate the neural underpinnings of divergent perception. A specifically designed divergent perception task was central to this investigation, allowing for an in-depth exploration of how individuals with varying levels of creativity engage with and interpret ambiguous stimuli.

Expanding the scope beyond scientific inquiry, the research-creation aspect of this thesis (chapters 4 and 5) investigates the auditory dimension of sensory ambiguity. Drawing on computational neuroscience, I examine how biological signals can be integrated into bio-art practices, focusing on embodied aesthetics and neuro-musical isomorphisms. The development of new sonification techniques as well as creative brain-computer interfaces (BCIs) are key components of this exploration. These BCIs are designed to leverage the complex nature of brain signals to create ambiguous sensory experiences, thereby facilitating the emergence of multi-stable auditory perceptions. By exploring the boundaries of perception and creativity, this thesis

seeks to contribute not only to academic discourse but also to practical applications in the fields of brain-computer interfaces and digital art.

From Divergent Thinking to Divergent Perception

Cognitive creativity

Cognitive creativity is often associated with the concept of divergent thinking, a term popularized by psychologist J.P. Guilford in the 1950s. Divergent thinking refers to the ability to generate multiple unique solutions to a problem, emphasizing nonlinear, associative thinking processes (Guilford, 1950). This form of creativity is central to problem-solving in various domains, from scientific innovation to artistic expression. In cognitive psychology, creativity is often studied through tasks that require novel associations, such as the Remote Associates Test (Mednick, 1962) or the Torrance Tests of Creative Thinking (Torrance, 1966). These tasks assess an individual's ability to think beyond conventional frameworks, a hallmark of cognitive creativity. Recent neuroscientific research has further illuminated the neural underpinnings of cognitive creativity. Studies using functional magnetic resonance imaging (fMRI) have associated creative thinking with the default mode network, executive control network, as well as regions responsible for emotional responses (Beaty et al., 2015, 2016, 2018; Kuang et al., 2022; X. Wu et al., 2015)(Beaty et al., 2016). This research suggest that cognitive creativity involves a complex interplay between spontaneous, associative processes and top-down executive functions. Cognitive creativity, with its focus on divergent thinking and problem-solving through novel associations, provides a crucial understanding of how we generate unique solutions and ideas. However, this perspective primarily emphasizes the conceptual and associative aspects of creativity, potentially overlooking the rich and nuanced role of sensory perception in the creative process. As noted by researchers such as Ramachandran & Hirstein (1999), the sensory

experiences and perceptual interpretations play a pivotal role in shaping creative outputs, a dimension that is not fully captured by cognitive creativity alone.

Perceptual creativity

Perceptual creativity, in contrast, can be seen as a parallel to divergent thinking, but in the perceptual domain. It involves finding multiple interpretations or solutions to a perceptual problem, rather than a conceptual one. Perceptual creativity emphasizes the immediacy and variability of sensory interpretation, whereas thinking processes often engage in abstract, sequential reasoning. This form of creativity is less explored but equally significant, especially in the fields of visual and auditory arts. Perceptual creativity is exemplified in the ability to perceive multiple interpretations in ambiguous stimuli, such as in the famous Rubin's vase, which can be seen both as a vase and as two faces (Rubin, 1915). This ability to toggle between different perceptual states indicates a flexible and creative perceptual system. However, little is known about the relationship between unconstrained pareidolia, where perceptions are not bound by specific task requirements or contexts, and creativity. This gap in knowledge extends to understanding how individuals with higher creative abilities may experience and interpret sensory ambiguity differently, and how these perceptual experiences might contribute to the creative process in a broader sense. The study by Diana et al. (2021) stands as a rare investigation in this area, examining how proneness to pareidolia is associated with individual creativity levels. Diana's work highlights the potential link between the frequency and intensity of pareidolic experiences and the overall creative capability of an individual, suggesting that those with higher creativity might be more attuned or responsive to ambiguous and abstract stimuli.

Entropy, central to complexity theory, plays a pivotal role in the interplay between creativity and perceptual processing, where higher uncertainty in sensory input can expand interpretative possibilities, thereby enhancing creativity (Gabora, 2016). This suggests that environments or

stimuli with higher levels of ambiguity and uncertainty can stimulate creative perceptual experiences. Chatterjee (2014) in 'The Aesthetic Brain' discusses how our evolution to appreciate beauty and art is intertwined with our ability to perceive and interpret complex, ambiguous stimuli. Supporting this notion, exposure to ambiguous stimuli was associated with both heightened levels of fluency, flexibility, and originality in tasks like the Alternative Uses Task and increased creativity in story generation tasks (X. Wu et al., 2019). This indicates that engaging with ambiguous stimuli can enhance creative capacities across different cognitive domains. Neuroscientific research provides further insights into these phenomena. For instance, studies on pareidolia have demonstrated significant activation in regions of the visual cortex and the imagination network (Liu et al., 2014a). This activation occurs when individuals perceive meaningful patterns in random stimuli, highlighting the intricate balance between sensory processing and higher-order cognitive functions. A recent meta-analysis has solidified the understanding that creative cognition is closely linked to perceptual abilities. This analysis highlights that bistable perception could be a key factor in enhancing creativity. It suggests that the process of perceptual reconfiguration, which necessitates flexibility mechanisms, may be integral to the development of creative thinking (Rodríguez-Martínez, 2023). In summary, perceptual creativity is deeply intertwined with the brain's handling of ambiguous sensory information.

Sensory Ambiguity in Vision and Sound

Visual Ambiguity: Gestalt principles

Visual information is processed by the brain through the optical nerve, and then being treated by primary visual areas, responsible for the processing of low-level features. The formation of higher-level constructs in the brain is done by secondary and associative visual areas, which integrate and interpret these basic features into coherent images and scenes. This process is deeply influenced by prior knowledge and contextual information. Hence, the same

visual information can lead to the identification of different percepts, based on inter-individual variability and active inferences about the surrounding context and previous experiences. Gestalt principles, first articulated by pioneers such as Koffka, Wertheimer, and Köhler (see Koffka, 2013; Wertheimer, 2017), provide a framework for understanding how our minds organize and interpret visual information. Gestalt psychology emerged in the early 20th century as a response to the then-dominant behaviorist and structuralist schools of thought. Koffka introduced the foundational principles of Gestalt psychology, emphasizing the idea that the whole is different from the sum of its parts. Wertheimer further developed these ideas, particularly focusing on the laws of organization in perceptual forms. Several key laws of organization in perceptual forms were identified, which are central to Gestalt psychology (see **Fig. 0.1**). These include the following laws:

- Proximity, stating that elements close to each other tend to be perceived as a group.
- Similarity, where similar elements are perceived as part of the same form or group.
- Closure, which describes our tendency to see complete figures even when part of the information is missing.
- Symmetry, highlighting that symmetrical elements are perceived together.
- Continuity, suggesting that our perception tends to follow a path that appears continuous or flowing.

Each of these laws plays a crucial role in how we organize and interpret visual stimuli, contributing to our understanding of complex images and patterns. These principles highlight the innate tendencies of our perceptual system to simplify and structure the visual world, often leading to a unique interpretation of ambiguous visual information. More recently, empirical findings have supported this approach by confirming the role of gestalt mechanisms in perceptual binding (Wagemans, Elder, et al., 2012; Wagemans, Feldman, et al., 2012). Gestalt principles have profound implications for creative perception. They suggest that artistic creativity can rely on the manipulation of visual ambiguity, guiding the viewer to alternate between different interpretations

of an image, what can be referred to as multistable perception. This phenomenon, where a single visual stimulus leads to multiple perceptual experiences, has been closely linked to creativity (Blake & Palmisano, 2021; Rodríguez-Martínez, 2023). This aspect of Gestalt theory offers valuable insights into the cognitive processes underlying artistic creativity and aesthetic appreciation. Consistently, a recent study demonstrated how exposition to ambiguous stimuli subsequently enhances performances at creative writing and divergent thinking tests (Wu et al., 2019). By understanding how our perception organizes and interprets visual information, Gestalt principles provide a framework from which creative potential can be tied to the processing of visual ambiguity.

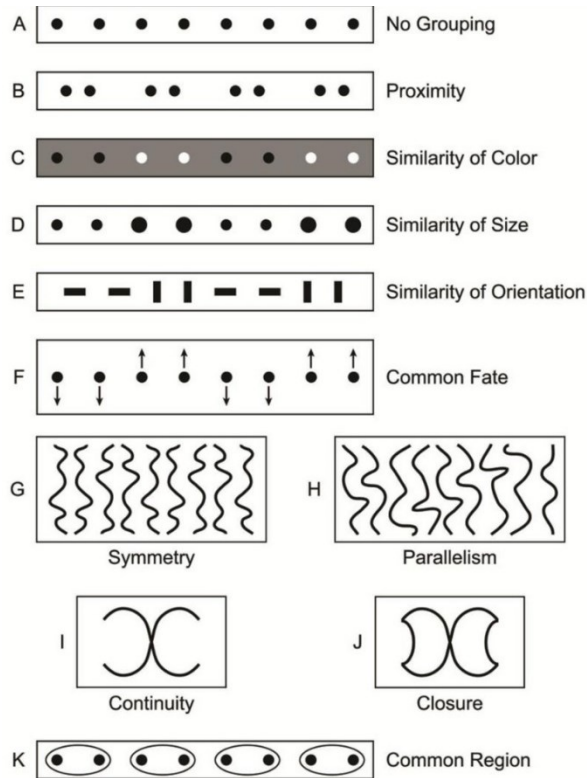


Figure 0.1. Illustrative examples of the principal grouping laws of Gestalt. (From (Wagemans, Elder, et al., 2012)

Auditory ambiguity in language

Auditory processing in humans is a sophisticated neurobiological function, enabling the interpretation of sound waves into meaningful information. This process begins with the transduction of sound waves into mechanical vibrations by the cochlea in the inner ear. These mechanical vibrations are then converted into electrical impulses, which travel via the auditory nerve to the brain. In the brain, these impulses undergo complex processing, primarily in the primary auditory cortices, where sounds are decoded and interpreted. This intricate mechanism not only allows humans to perceive a vast array of sounds but also plays a crucial role in communication and environmental interaction.

Auditory processing in the human brain differentiates remarkably between language and music, two primary categories of auditory experience. While both involve the decoding of complex sound patterns, the processing pathways and brain regions involved show significant differences (Steinbeis & Koelsch, 2008b, 2008a). Language processing primarily involves the left hemisphere, particularly areas known for linguistic comprehension and production, like Broca's and Wernicke's areas (Rutten, 2022). Music perception, on the other hand, engages a more diverse network across both hemispheres, in the processing of pitch, rhythm, and melody recognition (Peretz & Zatorre, 2005). Moreover, training on microtonal melodies has been associated with distinct changes in auditory cortex responses (Zatorre et al., 2012). This distinct neural allocation associated with the processing of musical stimuli highlights the brain's ability to specialize in processing different types of auditory information.

In language, auditory processing extends beyond mere sound recognition to the interpretation of symbolic representations – a phenomenon central to linguistic communication. These symbols, or phonemes, are the smallest units of sound in a language that can convey meaning. The brain's ability to associate specific phonemes with meanings is fundamental to

understanding and producing language. This symbolic representation allows for the construction of a vast vocabulary from a limited set of sounds. The complex cognitive process of linking sounds to meanings involves not only the auditory cortex but also regions responsible for memory and semantic processing, illustrating the deep interconnectivity within the brain during language comprehension (Friederici, 2011).

The human auditory system often encounters ambiguous signals, which it must resolve to derive meaningful perceptions. This phenomenon is strikingly exemplified by auditory illusions, such as the McGurk effect, which demonstrates how visual cues can alter the perception of auditory information, leading to a distinct experience from the actual auditory stimulus (McGurk & Macdonald, 1976). Auditory hallucinations, as observed in psychotic episodes and psychedelic experiences, provide a compelling example of how the brain interprets ambiguous auditory stimuli. These hallucinations, often triggered by an overload of sensory information, reveal the brain's tendency to construct meaning from noisy stimuli and underscore the influence of top-down processing — encompassing context, expectations, and prior knowledge — in shaping this interpretative mechanism. This phenomenon highlights the brain's persistent effort to identify patterns and coherence in the sensory inputs it receives, integrating multisensory information to resolve auditory ambiguities.

Auditory ambiguity in music

Auditory ambiguity in music presents a unique challenge for definition and comprehension, distinct from its linguistic counterpart, due to the inherent non-linguistic nature of musical elements. Unlike words, which carry specific meanings, musical elements often evoke a spectrum of interpretations and emotions. Tonal ambiguity is a property of musical auditory signals that is dependent on the strategic manipulation of pitch organization and harmonic structure (Bridges, 2012). In technical terms, it involves the use of complex and often unconventional intervals, chord

progressions, and scale modes that create a sense of uncertainty or fluidity in the listener's perception of the tonal 'ground' of the music. This concept is foundational in the composition and appreciation of many musical pieces, particularly in contemporary and experimental genres. The use of higher harmonics contributes to this ambiguity by introducing sonic elements that resonate at frequencies which, while harmonically related to the fundamental tones, introduce layers of complexity and uncertainty (see **Fig. 0.2.**). The familiar structure of a harmonic series is 'destructively' tested through the inclusion of prominent upper harmonic intervals, introducing a counterpoint of 'ambiguity' at the far end of a perceptual spectrum (Bridges, 2012). "The weighting of the contribution of individual pitches to its tonalness axis (from clarity to ambiguity) suggests a holistic role for microtonal materials (when salient), even if aspects of their individual structuring (i.e. scale structure) are less directly amenable to structural parsing and memorisation" (Bridges, 2012). This intricate interplay of harmonics enriches the auditory experience, allowing for a more dynamic and fluid interpretation of music, where the listener is engaged in a constant process of reevaluating and reinterpreting the tonal landscape. This very ambiguity could create a pronounced contrast between consonance and dissonance (simplicity and complexity), making microtonal intervals appealing for creative purposes when perceptually salient, as they can notably diminish unambiguous tonalness.

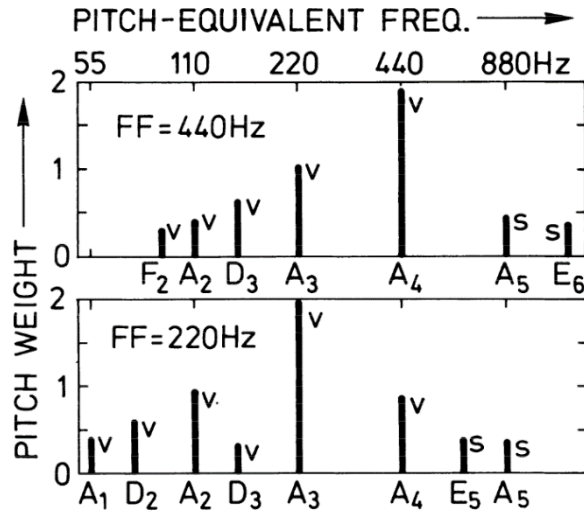


Fig. 0.2. Theoretical pitch patterns, on the second level of abstraction of two harmonic complex tones with fundamental frequencies 220 and 440 Hz. Virtual pitches: v; spectral pitches: s. Note ambiguity of pitch and partial coincidence of pitches in the two patterns. From Terhardt (1991)

Extending gestalt principles, traditionally applied to visual perception, to the realm of auditory perception offers a compelling framework for understanding how we interpret and make sense of auditory ambiguity in the context of music perception. Fundamental to this extension is the principle of figure-ground segregation (i.e. contourization), which in visual terms involves distinguishing an object (the figure) from its background (the ground). This principle finds its auditory counterpart in the way we process and segregate sounds. Contourization in music involves the abstraction and interpretation of the overarching shape or pattern of a melody or harmonic progression, distilling the essence of a musical phrase from its constituent notes and harmonies. This process mirrors the gestalt visual principle where the brain abstracts and recognizes shapes and patterns in the visual field. Further supporting this analogy between visual contours and auditory spectral pitches are various psychophysical phenomena. For example, contrast enhancement, known in vision as Mach bands, also finds an equivalent in auditory perception, where certain sounds can seem more distinct or emphasized in the context of surrounding sounds. Moreover, just as perceptions of shape, length, or direction of visual contours

can be systematically different from their objective parameters, creating visual illusions, a similar phenomenon occurs in auditory perception. An example of this is the subjective shift of spectral pitch, which can be influenced by factors like superimposed noise (Hartmann et al., 2019) or spectrally overlapping harmonic complex tones playing the role of masking frequencies (Micheyl et al., 2010). These effects demonstrate the brain's complex processing of auditory information, where subjective perception can differ from the objective characteristics of the sound.

Multistable perception in music refers to the phenomenon where a single auditory stimulus can lead to multiple, equally plausible perceptual interpretations. This is akin to the visual experience of an optical illusion where the brain alternates between different interpretations of the same image. In the musical domain, this phenomenon manifests when a piece of music allows for various interpretations of its rhythmic, melodic, or harmonic structure, often simultaneously. Two main sources contribute to this ambiguity in music: the insufficiency of structural information and contradictory structural information (Terhardt, 1991). The first, insufficiency of structural information, occurs when the music does not provide sufficient cues or clear direction for the listener to ascertain a definitive interpretation. This lack of clarity opens the door to multiple potential understandings of the music. The second source, contradictory structural information, arises when the music contains elements that suggest conflicting interpretations. This could be due to juxtaposing rhythms, harmonies, or melodies that seem to pull the listener in different directions, creating a sense of conflict or ambiguity in perception. It has been suggested that a certain degree of perceptual ambiguity enhances our appreciation of music (Pressnitzer et al., 2011). The enjoyment and emotional impact derived from music may partly stem from this interplay of clarity and ambiguity, challenging our auditory perception and inviting us to engage more deeply with the complex auditory scenes presented in musical compositions. More recently, auditory multi-stability has been investigated in relation to personality traits and executive functions, showing that individuals who frequently switch between alternative perceptions also

tend to have higher ego-resiliency, reflecting a broader tendency for adaptive flexibility and exploration of the auditory environment. Additionally, some aspects of these switching patterns are significantly associated with executive functions, indicating a link between cognitive control mechanisms and perceptual dynamics (Farkas et al., 2016).

To concretely illustrate the concept of auditory ambiguity in music, examining specific cases provide valuable insights. The Tritone Paradox, a phenomenon discovered by Deutsch (1991), involves a pair of tritone (six semitones apart) tones that are played sequentially. Depending on the listener, these tones can be perceived as ascending or descending in pitch, even though they are objectively equidistant in tonal space. This paradox highlights how individual perception can vary significantly, influenced by factors such as the listener's cultural background or even the specific tonal context they are accustomed to. The Shepard tone, another compelling example, involves a series of overlapping ascending or descending tones that seem to continuously rise or fall in pitch without ever actually getting higher or lower. This auditory illusion is created by playing a sequence of tones that are spaced one octave apart. As the sequence progresses, the volume of higher tones increases while the lower ones decrease, and new tones are added at one end of the sequence and removed at the other. The result is a seemingly endless scale that perpetually ascends or descends, tricking the ear into perceiving a continuous upward or downward motion. More recently, The Shepard tone has been extended to the creation of "perceptual melody auditory illusion" by using alternative spectral envelopes (Patrício, 2012). Furthermore, it has been shown that neuronal responses to Shepard's tones are characterized by multifractal behavior, supporting the idea that scale-free brain dynamics participate in the encoding of ambiguous auditory stimuli (Shimizu et al., 2007). Together, these examples support the idea that auditory ambiguity in music plays a crucial role in how we perceive and interpret harmonic and rhythmic structures in music.

Building on the foundational concepts of musical ambiguity, I will present two main concepts central to the research-creation component of this thesis. Microtonality, with its utilization of intervals smaller than the standard semitones, and polyrhythms, characterized by the simultaneous use of multiple rhythmic patterns, both serve to further challenge and expand the traditional boundaries of musical perception. Microtonality refers to the use of intervals smaller than the conventional semitones of Western music. This approach to music composition and performance expands the auditory palette, offering a vast array of pitches that lie outside the traditional twelve-tone scale. Pioneers in microtonal music, such as Alois Hába (1921) and Harry Partch (see Johnston, 1975), have explored these unconventional intervals, creating compositions that defy standard tonal structures. Microtonal systems have been further developed to establish a connection between mathematical principles and musical formalisms. This development is notably advanced by Erv Wilson's work on Moment of Symmetry scales (see Narushima, 2017), along with recent discussions highlighting the creative possibilities these systems offer, propelled by advancements in computer music technology (Burt, 2023). The perceptual impact of microtonality is profound. It challenges listeners to engage with unfamiliar pitch relationships, thereby enhancing their auditory discrimination and creative interpretation. Recent work have explored the cognitive aspects of tuning systems, shedding light on how microtonality can alter auditory perception (A. Milne, 2018; A. J. Milne, 2013; Sethares, 2005a). By increasing the granularity of musical notes, microtonality allows for the creation of ambiguous harmonies.

Rhythmic complexity, or rhythmic tension, encompasses both the concepts of syncopation, representing small deviations from the expected rhythmic structure, and polyrhythms, involving the simultaneous use of two or more confluent rhythms (Vuust et al., 2014; Vuust & Witek, 2014). The perception of polyrhythmic structures as ambiguous is influenced by an individual's prior exposure to complex rhythms and their level of musical expertise. Research

has demonstrated that musical expertise enhances the endogenous oscillations linked to the perception of complex rhythms, a phenomenon known as neural entrainment (Stupacher et al., 2017). Unlike the regular and predictable rhythms found in much of Western music, polyrhythms create a complex and often unpredictable auditory experience. This rhythmic complexity can be seen as a form of auditory ambiguity, as it presents listeners with multiple, simultaneous rhythmic interpretations. The creative implications of polyrhythms are significant. They challenge the listener's rhythmic perception, opening new avenues for creative expression in music composition and performance. The use of polyrhythms has been a staple in various musical traditions around the world, contributing to the rich diversity of global music.

In this thesis, I explore the roles of microtonality and polyrhythms in navigating auditory ambiguity, highlighting innovative approaches that leverage the intricate and inherently ambiguous nature of biosignals to craft meaningful musical components.

Converging Neurosciences and Bio-arts

The Role of Intuition in Transdisciplinary Discoveries

Intuition is a critical component of creative problem solving, serving as an essential complement to analytical thinking (Policastro, 1995; Raami, 2015). Contrarily to popular views that effective solutions emerge from purely explicit and rational thinking, gut feelings, often rooted in unconscious processing, can lead to effective decision-making, especially in complex situations (Gigerenzer, 2007). Furthermore, the theory of unconscious thought provides a framework for understanding how intuition operates, proposing that the unconscious mind is capable of processing complex information in ways that the conscious mind cannot (Dijksterhuis & Nordgren, 2006). This process often leads to intuitive insights crucial in creative and innovative endeavors (Creswell et al., 2013; Zhong et al., 2008).

In transdisciplinary research, where various fields of knowledge converge, intuition acts as a bridge, connecting different domains of expertise and fostering innovative solutions to complex problems (Madni, 2007; Pearce et al., 2022). This aspect of intuition enables a leap from the typical solution space of a given field into regions of the solution space of another field. A recent model suggest that insights in transdisciplinary discoveries require “new ways of knowledge production” (Lang et al., 2012), learning from a wide range of disciplines and often the inclusion of knowledge from outside of academia (Pearce et al., 2022), what is also called “translational knowledge” (Ciesielski et al., 2017). By gaining cross-disciplinary information, researchers become able to frame better questions (Ciesielski et al., 2017). In transdisciplinary processes, the goal is to foster a gap-filling mechanism, similar to the gestalt, where the pursuit of separate elements forms an understanding that is more expansive than merely the aggregate of its parts, leading to an emergent comprehension of the whole.

Intuitive knowledge gained through transdisciplinary practices is considered a method for reshaping our original mental models to better match collective objectives (see **Fig. 0.3.**). This approach encourages us to realign our goals with a wider context, which is especially relevant in today's ecological crisis. By doing so, we extend our sense of kinship to encompass the entire ecosystem we inhabit, fostering a deeper connection with our shared environment. In this context, there is a necessity for transdisciplinary researchers to cultivate 'curiosity about, and willingness to learn from others' (Pearce et al., 2022). This includes recognizing the discomfort that may come with stepping outside one's intellectual comfort zone, suggesting that such openness and adaptability are essential for addressing complex ecological challenges. Consistently, recent work emphasizes the role of creativity and inter-subjectivity in the enhancement of translational ecologies (Goeltzenleuchter et al., 2019).

One proposed mechanism for fostering translational creativity across diverse fields is through the concept of embodied or "felt knowledge," (Henriksen et al., 2015). This approach

emphasizes "proprioceptive thinking," where individuals utilize their bodily sensations—such as muscle movement, balance, and tension—as a dynamic tool for cognitive reasoning and the generation of new insights. In such context, cues from different sources can be tied together, such as those between psychomotor and semantic, or perceptual and conceptual dimensions of experience. By grounding the cognitive process in the body's experiences, proprioceptive thinking enables the construction of novel knowledge that transcends disciplinary boundaries, leading to creative translations and innovations between fields (Henriksen et al., 2015).

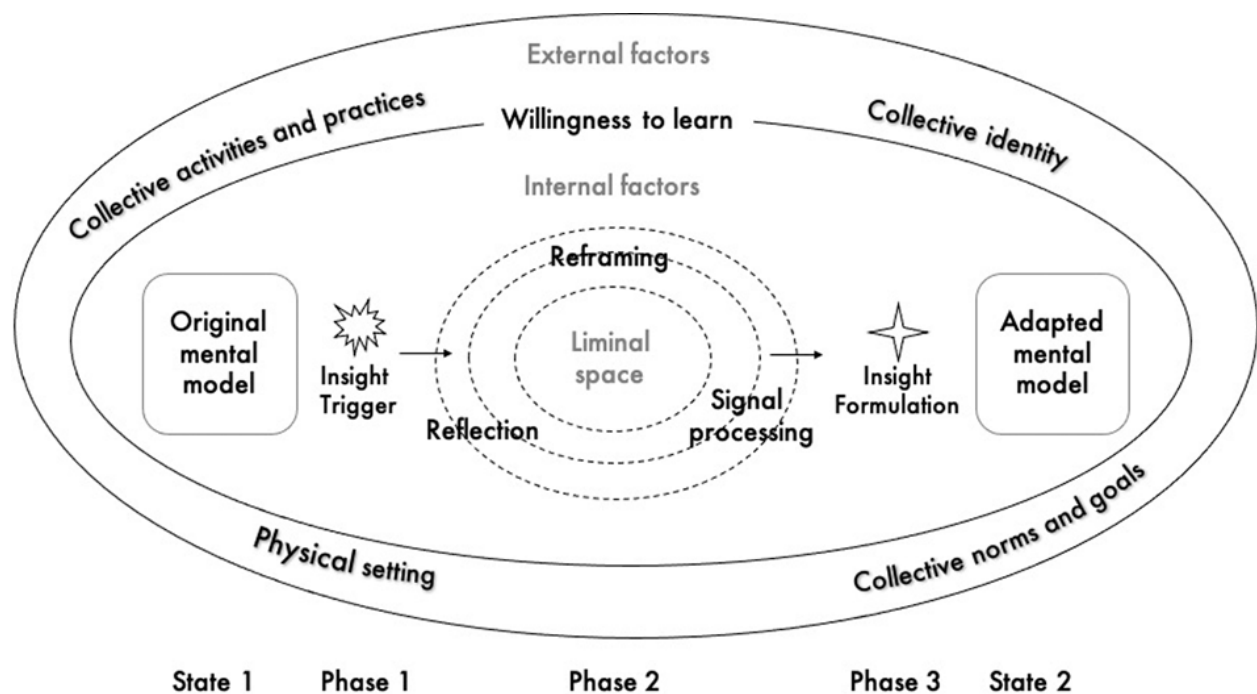


Figure 0.3. The process of insight in transdisciplinary research. The process begins with the original mental model (State 1), which is disrupted by an insight trigger (Phase 1), moves into a liminal space characterised by reframing, reflecting and signal processing (Phase 2), leads to insight formulation (Phase 3) which contributes to an adapted mental model of the problem or situation (State 2). (from Pearce et al., 2022)

In this thesis, I build intuitions from the intersection of the fields of neurosciences and music theory, exploring new ways of probing creativity in terms of its neural underpinning (rationally) and using biosignals as a source of creative expression (intuitively). By focusing on the collaborative synergy between neuroscience and mathematical models of harmony, this thesis aims to illuminate how musical interpretation of electrophysiological signals can both contribute

to the evolving landscape of bio-art and can inspire the development of analytical tools in computational neuroscience. Hence, perspectives brought by the general framework of signal processing methodologies enables a fluid exchange of ideas and approaches between neuroscience and music theory. This exploration is driven by transdisciplinary analogies, where technology serves as both a catalyst and a canvas for artistic practices, while simultaneously, the artistic manipulation of technology fosters advancements in scientific understanding. This symbiotic dynamic accentuates a narrative where intuition and scientific knowledge enter in dialogue, enhancing artistic endeavors and offering novel insights into the complex relationships between music, technology, and the creative brain.

The scientific investigation of divergent perception

In this thesis, I will systematically explore the relationship between sensory ambiguity and creativity, with a specific focus on the phenomenon of pareidolia—a perceptual experience where recognizable patterns are identified in ambiguous stimuli. The first chapter lays the foundational understanding of this relationship by conceptualizing "divergent perception," a parallel to the well-established concept of divergent thinking in creativity research. We argue that pareidolia, often triggered in altered states of consciousness, aligns with various theoretical frameworks of creativity, including cognitive disinhibition and evolutionary algorithms. This chapter aims to provide an intuitive understanding of how perception, particularly when altered, intertwines with creative processes, and sets the stage for empirical investigation. The second chapter delves into empirical research, where we examine the perceptual aspects of creativity by exploring whether individuals with high creative abilities are more inclined to experience pareidolia. Through a novel visual task involving fractal images, this research seeks to establish a connection between the frequency of pareidolic perceptions and the level of creativity, thereby extending our understanding of divergent thinking to include divergent perception. The third chapter advances this exploration by identifying the neural correlates of unconstrained pareidolia. This involves

comparing brain activity during pareidolic states with non-pareidolic states, investigating the interplay between properties of visual stimuli and brain activity, and assessing how these dynamics are modulated by varying levels of creativity. Additionally, this chapter examines the changes in spontaneous brain activity in response to pareidolia tasks and explores the influence of suggestion on pareidolic perception, adding a new dimension to our understanding of how belief or expectation can shape perceptual experiences. Through these investigations, the thesis aims to shed light on how creativity extends beyond mere cognitive processes to the way the brain dynamically constructs meaning through perceptual processes.

The creative exploration of biosignals .

Building on the scientific investigation of divergent perception, where we examine the role of pareidolia in creative processes, this thesis incorporates a research-creation component that delves into the auditory exploration of biosignals. This shift from visual to auditory realms represents a natural progression in our exploration of sensory ambiguity and creativity. Just as pareidolia demonstrates the brain's capacity to find order in visual chaos, the sonification of electrophysiological data presents a parallel avenue in the auditory domain. Here, I delve into how biosignals can be transformed into complex multistable musical structures, thereby exploring new forms of auditory ambiguity. This innovative approach, which interweaves neuroscience and music, offers a fresh perspective on the relationship between neural activity and auditory experiences.

Biosignals, in their broadest definition, encompass a variety of physiological signals generated by the body, such as electrocardiograms (ECG), electromyograms (EMG), and electroencephalograms (EEG). These signals, derived from the heart, muscles, and brain respectively, offer a diverse range of patterns and rhythms inherent in biological systems. Their exploration is particularly relevant in understanding the complexity of biological processes, as

they are known to exhibit nonlinear dynamics (Klonowski, 2006; Natarajan et al., 2004) and scale-free dynamics (Boonstra et al., 2013; Deppman & Andrade-II, 2021; Muthukumaraswamy & Liley, 2017). The inherent complexity of biological systems, characterized as operating near-criticality (de Arcangelis et al., 2006; O'Byrne & Jerbi, 2022a), provides a rich source for emergent music. This complexity, being simultaneously flexible and structured, leads to emergent behaviors, making biological processes ideal models for exploring new musical formalisms. By translating varied physiological rhythms and patterns into sound, we create a window onto the intricate dynamics present in nature, thereby embedding their emergent properties into perceptible musical forms.

Bioacoustics corresponds to the study of the production, transmission, and reception of sounds in animals, including humans. This field has inspired the creation of new musical instruments and sound synthesis techniques, drawing from the activity in living organisms (Erkut, 2004; Smyth & Smith, 2001). It provides a unique lens through which we can understand how living beings interact with their environment through sound. In the context of this thesis, I expand this concept to include the sonification of biosignals, particularly those related to brain activity, to construct new musical instruments and structures. This extension leads me to propose the concept of neuroacoustics, standing at the intersection of bioacoustics and electroacoustics, defined by the transformation of brain electrical signals into musical formalisms. Such a transformative approach allows exploring the musicality of brain activity while challenging our traditional notions of musical composition and perception. This process goes beyond mere artistic novelty; it reveals the deep-seated connections between our neural processes and how we experience and create music.

The sonification of EEG data has opened novel pathways to understanding the creative potential of brain signals. Research in this area has shown that transforming EEG signals into sound can provide deep insights into the relationship between auditory experiences and neural

activity (Sanyal et al., 2019). The relationship between complexity of biosignals and aesthetic preferences in music has also been a focus of study, revealing a general preference for compositions derived from $1/f$ processes, such as biosignals, which offers a balance between predictability and surprise (Levitin et al., 2012a). This preference extends across various musical genres, including hip-hop, new-age, and jazz (W. Ro & Kwon, 2009). Wu et al. (2009) took this concept further by sonifying brain signals using translation rules that map EEG waveform characteristics to musical elements, demonstrating that music derived from REM recorded during sleep was perceived as emotionally more positive than that derived from white noise. Projects like Bell & Gabora (2016) generative musical algorithm, which operates 'at the edge of chaos', and Bown's (2009) ecosystem-based generative music, aim to produce complex outputs that are both pleasing and beyond the user's understanding. These approaches to algorithmic composition emphasize the use of statistical properties of a system over time to achieve complex and aesthetic musical results.

The research-creation component of this thesis builds on the conceptual framework of these previous work by centering on biological ambiguity as a catalyst for creative expression. It particularly focuses on the sonification of EEG data, a rich source of uncertainty and surprise. This approach aligns with work that posit ambiguity as a key element in the perception and creation of meaning (Abergel, 2019; Chiu & Shu, 2012; Levinson, 2000; Mehta et al., 2012; X. Wu et al., 2019). Drawing upon neurophenomenology (F. J. Varela et al., 2017) and gestalt theory (Koffka, 2013), the research investigates the creative potentials embedded within the ambiguity of biological processes as a way of conveying musical meaning. This inquiry is informed by the interplay of predictability and unpredictability in stimuli interpretation, akin to the perceptual phenomena of pareidolia (Diana et al., 2021) multistability (Chen et al., 2023; Kruse & Stadler, 2012). Such phenomena illustrate how ambiguity in sensory information can lead to diverse perceptual and cognitive interpretations, offering a rich palette for artistic exploration.

The use of creative brain-computer interfaces (BCIs) serves as a bridge between the complex neural activities of the brain and potential artistic representations, integrating feedback mechanisms into the bio-inspired generative processes of music creation. Inspired by the concept of 'neuroaesthetics' (Brattico & Pearce, 2013; M. T. Pearce et al., 2016), this approach seeks to understand and utilize the brain's responses to aesthetic experiences, transforming them into novel artistic forms, that will in turn influence the subsequent brain responses.

In essence, the two last chapters of this thesis delve into the depths of biological ambiguity, applying musical theory to the study of electrophysiological signals, harnessing its potential to create art that resonates with the complexities and subtleties of human perception and cognition. Through this exploration, we aim to uncover new ways in which the brain's intricate processes can be artistically interpreted and represented, contributing to both academic discourse and practical applications in digital art and brain-computer interface technology.

Divergent Perception: The Role of Ambiguous Sensory Information in Creative Cognition

Abstract

Creativity is a cornerstone of human evolution and is typically defined as the multifaceted ability to produce novel and useful artifacts. Although much research has predominantly focused on divergent thinking, growing evidence indicates the significant role of perceptual abilities in fostering creativity. The present work intends to provide an intuitive understanding of how (altered) perception and creativity are related. In doing so, I contextualize the phenomenon of pareidolia, which involves seeing familiar patterns in noisy or ambiguous stimuli, as a key perceptual mechanism of idea generation—one of the central stages of the creative process. I argue that pareidolia aligns well with various theoretical frameworks of creativity, including cognitive disinhibition, evolutionary algorithms, and spontaneous/deliberate modes of creativity. As a result, I propose "divergent perception" as a perceptual parallel to divergent thinking and illustrate how this concept could account for the heightened creativity observed in psychedelic and psychotic states. In conclusion, future methodologies for the exploration of divergent perception are highlighted, emphasizing the manipulation of stimulus characteristics and attention mechanisms.

Introduction

"Savoir regarder est un moyen d'inventer." *Salvador Dali*

Creativity is foundational in knowledge development and helps humans in adapting to their environment. A widely held definition of creativity is the ability to produce work that is both novel (i.e., original, unexpected) and appropriate (i.e., useful, adaptive concerning task constraints) (Sternberg & Lubart, 1998), though this definition lacks multidimensionality (Barbot et al., 2015; Dietrich, 2007; Fryer, 2012; Glăveanu, 2014). While many neuroscientific theories of creativity have been proposed during the past decades (Dietrich, 2004; Jung et al., 2009; Simonton, 2010a; Wiggins, 2006), no consensus regarding fundamental creative processes has emerged from these theoretical backgrounds (Dietrich & Kanso, 2010; Sawyer, 2011). Divergent thinking, defined as the ability to generate multiple solutions to an open-ended problem (Guilford, 1950, 1967), has been the most widely used measure of creative abilities (Weisberg, 2006). The Torrance Tests of Creative Thinking (TTCT), the most widely used measure of creativity, is primarily constituted by divergent thinking tests (Kim, 2006). Two major problems arise when considering divergent thinking tests as a measure of creativity (Dietrich, 2019a, 2019b): (1) as its opposite – convergent thinking – can produce creative ideas (Simonton, 2015a), it becomes unclear what is distinctly creative in divergent thinking. (2) divergent thinking is a compound construct, leading to assessing multiple facets and mental processes within the same measurement (Ward et al., 1999). These problems demand caution when approaching creativity as a monolithic entity (Dietrich, 2019b). These caveats of the empirical developments in neuroscientific research of creativity encourage finding new ways of operationalizing this multifaceted concept.

Another main theoretical approach to creativity divides its temporal sequence into two phases: idea generation and idea selection (Simonton, 2010a). From an evolutionary perspective,

these phases correspond to the variation and selection processes, respectively. The general idea is that the generation phase is mostly characterized by unstructured behaviors and richness of experience (i.e. divergent processes), while during the evaluation phase, constraints are refined while critical thinking and higher cognitive functions such as metacognition are deployed (i.e. convergent processes). Different altered states of consciousness have been associated with enhanced creative idea generation, such as the psychedelic state (Baggott, 2015; Gandy et al., 2022; Girn et al., 2020; Hartogsohn, 2018; Prochazkova et al., 2018) and psychotic episodes (Carson, 2011; Fink et al., 2014; Sandsten et al., 2018), while no underlying mechanism has been identified to explain this shared phenomenological outcome. While extensive research has been conducted on the neural and cognitive processes associated with creativity, a significant knowledge gap persists, especially in understanding the interplay between altered perceptual experiences and creative idea generation. A critical examination of the literature and state of the art is needed to push forward our comprehension of how divergent perceptual states impact creative cognition.

In this work, I explore the deep theoretical connections between creative idea generation and the integrative processes underlying the perception of ambiguous stimuli (pareidolia). Furthermore, the concept of divergent perception, the perceptual counterpart of divergent thinking, is introduced as a potential mechanism leading to creative idea generation. This Perspective is segmented into seven sections. First, the intertwined relationship between perception and creativity are highlighted. The second section introduces the concept of pareidolia as a perceptual counterpart of divergent thinking. Thirdly, leveraging an evolutionary perspective, the commonalities between pareidolic perception and variation-selection process are discussed. The fourth section puts forth aberrant salience as a potential mechanism that might account for the observed connections between creativity of both psychotic and psychedelic experiences. Next, I discuss parallels in the brain network dynamics that underpin creativity, altered states of

consciousness and divergent perception. In the penultimate section, I introduce the concept of 'emergent narratives', suggesting its potential as a connector between pareidolic perception and creative outputs. Our concluding section presents new experimental directions for investigating divergent perception.

Creativity and perception

When perception and imagination overlap

Our ability to create depends heavily on our ability to perceive and model the external world (Heath & Ventura, 2016a), suggesting that creative individuals see the world differently (Flowers & Garbin, 1989). Perception is a *sine qua non* condition of creativity, since an individual that has never perceived or experienced the external world could not interact with it and has no reference to build from, hence making it nearly impossible to produce novel and useful ideas. From this perspective, perception and creativity are inherently coupled. Recent findings indicate that imagined and perceived signals blend together, with the assessment of what is real hinging on whether this combined signal is intense enough to exceed a reality threshold (Dijkstra & Fleming, 2023). Additionally, Vygotsky (2004) emphasizes that perception naturally aligns with imagination, a pivotal process that catalyzes creativity by forging new artifacts. The definition of imagination provided in the Oxford English dictionary underscores the close relationship between imagination and the process of perception:

The power or capacity to form internal images or ideas of objects and situations not actually present to the senses, including remembered objects and situations, and those constructed by mentally combining or projecting images of previously experienced qualities, objects, and situations. Also (esp. in modern philosophy): the power or capacity by which the mind integrates sensory data in the process of perception. (Oxford Dictionary, 2022)

Modern views on imagination confer its central role in human perception as it deals with “variations and uncertainty in the natural and cultural environment” (Pelaprat & Cole, 2011). The overlap between brain patterns during perception and imagination has been demonstrated in neuroscientific studies. Ibáñez-Marcelo et al. (2019) used EEG to study the functional overlap between mental imagery and real sensori-motor perception. They found varying degrees of equivalence among individuals, with some showing closer alignment between perception and imagination tasks, suggesting a learning effect. Similarly, Berger & Ehrsson (2014) used functional magnetic resonance imaging (fMRI) to investigate the interaction and integration of the senses in mental imagery. They found that mental imagery changed multisensory perception and that there was functional and neuroanatomical overlap between imagery and perception.

In this context, imagination can be seen as a way to fill gaps in sensory experiences for the purpose of attributing meaning to them. This model updating process helps to create and preserve the plausibility of experiences by simultaneously drawing on internal models and simulating potential future actions. As a result, imagination is not solely associated with internal representations detached from sensory input; rather, it may lead to active inferences regarding future embodied states. Consequently, it is tempting to frame creative behavior as an interactive process that is driven by the way we integrate sensory experiences with internal representations of the world through imaginative perception. This interplay between perception and imagination naturally leads us to consider how our subjective experiences are embedded and intertwined with the external world.

Phenomenology of perception and Gestalt theory

The phenomenology of perception, initially elaborated by Merleau-Ponty (1965), is a philosophical approach that conceives subjective experience as being fundamentally embedded in the external world, as opposed to a view of subjectivity as a remote and autonomous process occurring specifically inside the brain. From this viewpoint, the emergence of ideas is the result

of interactions with the environment, hence pointing to the intrinsic relation between perception and knowledge. In his work, Merleau-Ponty conceptualizes creativity as “being operative from the basic level of pre-conceptual knowledge in perception up to more complex forms of conceptual and predicative knowledge.” He considers the phenomenon of attention as “the first creative moment that allows the formation of knowledge” (Summa, 2017). By determining the shaping of experience, attention guides perception and acts as a catalyst for the emergence of meaning. Furthermore, (Merleau-Ponty, 1969) insists on the concept of Gestalt as a fundamental aspect of creative thinking. Gestalt theorists explained perception by suggesting characteristic and intrinsic laws governing its occurrence. Their vision resulted in the popular saying that “the whole is [perceptually] more than the sum of its parts”. Empirical findings support this approach by confirming the role of gestalt mechanisms in perceptual binding (Wagemans, Elder, et al., 2012; Wagemans, Feldman, et al., 2012). Gestalt theory supposes that holistic mental representations emerge from everyday perception, hence highlighting the inherent creative properties of perceptual processes. “If perception is organized according to Gestalt laws, it must be regarded as creative by nature” (Nęcka, 2011). Building on this view, modern Gestalt therapy developed tools for exploring creative processes (Amendt-Lyon, 2001).

The Gestalt theory has faced criticism for its lack of parsimony, which is reflected in the numerous perceptual laws that have been proposed to explain the formation of perception. To summarize such instances, Lehar (2003) identified emergence, reification, multistability and invariance as core Gestalt properties of perception. Emergence encompasses the phenomenal property of a stimulus, and relates with stimulus properties, such that the local information does not provide an accurate representation of the global information pattern. Reification involves “filling in the gaps” and necessitates the projection of internal representations and top-down processes. Multistability exhibits the ability of a stimulus to be perceived as multiple objects. Lastly, invariance refers to the capacity of the internal representation/concept (the underlying

cause) to remain identifiable across diverse stimuli (see **Fig 1.1**). An example distinguishing multistability and invariance can be seen in the classic Rubin's vase illustration: multistability occurs as our perception shifts between seeing a vase and two faces in profile, depending on which aspect of the image we focus on, demonstrating the ability of a single stimulus to lead to multiple stable interpretations. In contrast, invariance is illustrated by our ability to recognize the concept of a "face" or a "vase" across various representations, whether the image is detailed, abstract, or viewed from different angles, showing how the fundamental essence of the object remains constant in our perception despite changes in the visual input.

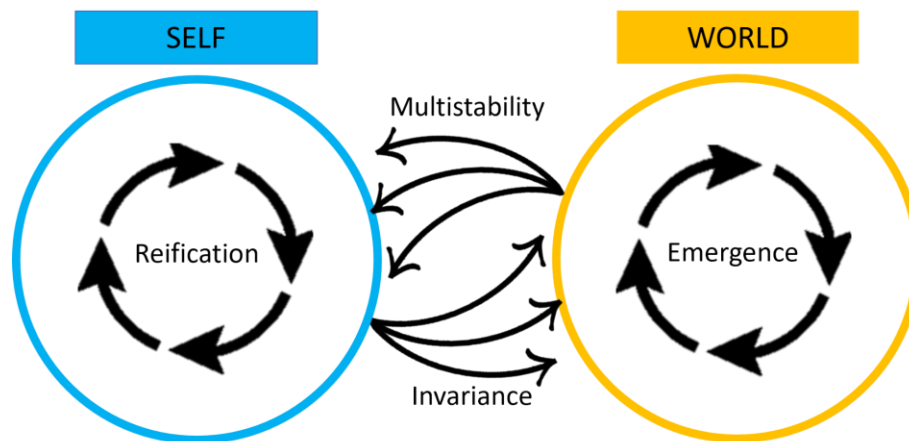


Figure 1.1 Gestalt mechanisms. Inspired by the model of Lehar (2003)

From the Gestalt perspective, ambiguity in physical stimuli acts as a fertile ground upon which imagination can project, catering to the human need for deriving meaning. This ambiguity is central to understanding creative perception. When presented with ambiguous stimuli, the brain is challenged to reconcile this uncertainty, often resulting in the synthesis of creative ideas by connecting disparate sensory information or elements of the perceptual experience. One way to measure the level of ambiguity in stimuli is by examining their multistable nature. Multistable perception refers to the phenomenon where ambiguous stimuli can give rise to multiple, alternating interpretations. It has been posited that multistable perceptions facilitate the

emergence of meaning, which is known to build upon self-referential processes in cognitive systems (Kruse & Stadler, 2012). In support of this idea, a study utilizing the Rorschach inkblot task (Schott, 2014) was conducted where participants attempted to discern cohesive images from ambiguous forms. Their ability to coherently perceive these forms showed a significant correlation with peer-rated creativity (Nęcka, 2011). Moreover, the ability to alternate between different versions of a multistable percept has been associated with divergent thinking (Blake & Palmisano, 2021; Rodríguez-Martínez, 2023). Interestingly, Torrance (1962) represented the origin of creativity as an impression that a gap has to be filled, a sense of unfulfillment, which resembles the gap-filling mechanism characteristic of gestalt.

Top-down Influences on Divergent Perception

The effect of internal states on perception is well known and exemplified by Gestalt theory, as well as by studies investigating the role of top-down processes in the emergence of integrated percepts (Kok et al., 2012; Pascual-Leone & Walsh, 2001; T. Ro et al., 2003; Vetter et al., 2014). Perceptual decision-making is known to be affected by both sensory and decisional choices biases (Linares et al., 2019). Higher-order representations and expectations based on prior knowledge are components of the subjective experience affecting the way sensory information is treated. It is known that subjective experience affects the processing of sensory information particularly in the context of ambiguous stimuli, possibly as a result of meaning-seeking (Gendlin, 1997). Interestingly it has been demonstrated that under perceptual uncertainty, individuals with higher levels of mental imagery (i.e. the experience of “seeing” with the mind’s eye) are more prone to anomalous perception, emphasizing the link between the richness of one’s internal visualizations and their susceptibility to perceptual distortions or illusions (Salge et al., 2021).

For example, physiognomic perception, defined as the ability to perceive affect in inanimate things (Nęcka, 2011), is one phenomenon that results from this projection of mental states onto external objects. It has been demonstrated that individuals scoring higher on the

Remote Association Test—a common measure of creativity—are more prone to report experiencing physiognomy (Dailey et al., 1997; Kaufman & Kaufman, 2009). These perceptions, such as feeling that the sun is “sad” or that the wall has “ears”, are subjective experiences anchored in perceptual processes and are thought to facilitate the emergence of new ideas, possibly through narrative integration. Hence, physiognomic perceptions are a specific case that exemplifies how ambiguous sensory information may promote creative exploration through top-down influences and projections of internal representations into the perception of the external world. Pereira & Tschimmel (2012) suggest that creativity emerges from three distinct types of perception: confused, as evidenced by psychotic symptoms; malfunctioning, illustrated by sensory impairments like Beethoven's deafness; and intentional, steered by expertise and analogical reasoning. The rationale behind this association between impaired perception and creativity is that an increase of sensory uncertainty facilitates a process of filling-in, which in turn potentially leads to the formation of innovative points of view.

Embodied creativity

Recent insights into embodied cognition propose a novel perspective on creativity, emphasizing its roots in perception and environmental interaction. Malinin (2019) advocates for the inherent interconnectedness of action and perception in creativity, challenging the traditional subject-object dichotomy. This ecological approach to perception underscores the dynamic interplay between the observer and the observed, where perception is not merely a passive reception of information but an active, exploratory process shaped by one's potential actions within an environment (Witt & Riley, 2014). Against this backdrop, creative performances can be dissociated from creative experiences, which are subjective and anchored in perception (Fischer & Scheib, 1971). In its psycho-cultural perspective on creativity, Gabora (2017) posits that creative individuals are primarily characterized by their worldviews, giving to the creative product a secondary importance, and pointing to the importance of how subjectivity interacts with the

environment in the emergence of creative endeavors. Building on this, D'Angelo (2020) delineates the role of attention in modulating experiential fields, hinting at its potential impact on creative processes.

Hargreaves (2012) points to the necessity of studying creativity through perception and suggests that music listening (intentional perception) is at the core of the creative process. Supplementary studies on improvisational actions (Baber et al., 2019; Pereira & Tschimmel, 2012) and autistic spectrum disorders (Kiou, 2018; Leong, 2012) fortify this perspective, portraying creativity as an emergent, distributed phenomenon deeply anchored in perceptual processes. Studies on savant syndrome show the contribution of augmented perceptual sensitivity and pattern recognition capabilities in the extraordinary creative talents observed in these individuals (Mottron et al., 2009; Treffert, 2009). In summary, this body of research underscores the profound implication of perception, and its interaction with the environment, in the genesis of creative thought.

Insights from artificial intelligence on the nature of divergent perception

At its core, creativity in machines, much like in humans, revolves around the ability to perceive the world in novel ways and generate responses that are both original and appropriate. Learning algorithms inspired from models of the brain exemplify how creativity relates to perception. To generate novel and relevant output, a generative model must first internalize representations from reality (Heath & Ventura, 2016a). The DeepDream program was one of the first instance of deep learning algorithms' capability to produce creative visual outputs grounded in learned perceptions (DiPaola & Gabora, 2009; Keshavan & Sudarshan, 2017; Kitson et al., 2019; McCaig et al., 2016; Suzuki et al., 2017). It operates by inputting an image into the neural network and incrementally adjusting the image to accentuate the features recognized by the network, creating surreal, dream-like visuals. Schmidhuber (2010) offers another pivotal perspective by examining intrinsic rewards in reinforcement learning and computational models.

He suggests that the quest for creativity is essentially a search for unexpected patterns, and when these patterns are found or created, they lead to a surge in intrinsic reward. These novel patterns, when decoded, enable optimization in data representation and compression. In essence, clarifying ambiguous sensory data bolsters predictive accuracy regarding world states. This viewpoint situates creativity as the pursuit and appreciation of emerging patterns, identified through sensory experiences or actions, resulting in more streamlined data interpretation.

Taken together, this section highlights the fundamental role of ambiguous perception in creativity. Thus, both work in phenomenology and Gestalt, as well as research in embodied cognition and in artificial intelligence, suggest that paradigms studying creativity should introduce perceptual mechanisms into their model.

Pareidolia: a measure of divergent perception

Understanding the nuances of human creativity entails delving into both cognitive and perceptual territories. Historically, neuroscience research hasn't extensively probed the intersection of perceptual tendencies and creative abilities (Flowers & Garbin, 1989). A pivotal study by Wu et al. (2019) illuminated this relationship, uncovering that exposure to ambiguous stimuli not only heightened levels of fluency, flexibility, and originality on the Alternative Uses Task but also increased creativity in story generation tasks. Crucially, the exposure to ambiguity appeared to foster enhanced remote associations, suggesting a facilitative link between perceiving ambiguity and making creative connections (Beghetto, 2019; Beghetto & Jaeger, 2022). In support of this finding, people with high divergent thinking abilities are more capable and rapid in finding alternative interpretations to ambiguous figures (Bellemare-Pepin et al., 2022; Diana et al., 2021; Riquelme, 2002). Additionally, creativity in general is known to influence visual perception even at the earliest stage (Csizmadia et al., 2022). Such findings lay the foundation for a compelling hypothesis: Creativity might transcend mere cognitive processes, binding closely

with perception of ambiguity. In other words, the way individuals perceive and interpret the world around them could significantly shape their creative output and abilities.

In this context, pareidolia could serve as an ideal representation of creativity's perceptual dimension. Pareidolia involves discerning recognizable patterns or objects in ambiguous stimuli, like discerning shapes in cloud formations (Petchkovsky, 2008). Evolutionary theories posit that this phenomenon was instrumental for early hominids, facilitating the detection of potential threats in complex sensory landscapes (Barrett, 2000; Meschiari, 2009), as well as fostering metaphysical and creative thought (Parker, 2023). Notably, when our brain encounters such ambiguous stimuli, it faces a choice: to dismiss the patterns as mere noise or to evoke pareidolia, drawing connections between the perceived ambiguity and stored memory concepts. These pareidolic interpretations, however, are not mere reproductions of past perceptions but are crafted from the interplay between sensory input and the activation of related semantic concepts.

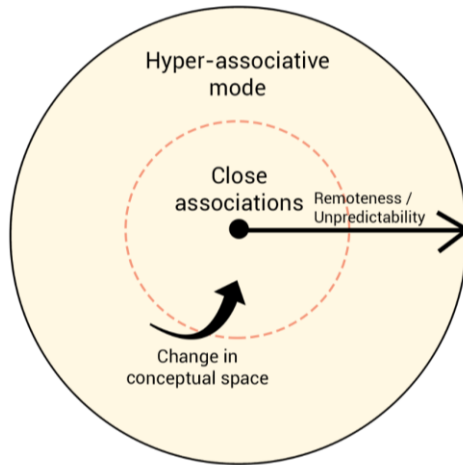
Contemporary anecdotes underscore pareidolia's enduring influence on creativity. Renowned artists have consistently cited it as a muse. As exposed in (Gamboni, 2002) work *Potential Images*, Piero di Cosimo inspired his painting by looking at the sky, Novalis wrote about figures he saw in the clouds, and Chinese painter Sung Ti used the technique of looking at a tumbledown wall covered by a thin piece of white silk. "You gaze at it until you can see the ruins through the silk, its prominences, its levels, its zig-zags and its cleavages, storing them up in your mind, and fixing them in your eyes. Soon you will see men, birds, plants and trees, flying and moving among them. You may then ply your brush according to your fancy" (Gamboni, 2002). Leonardo Da Vinci even advocated for observing clouds, rock formations, and stained surfaces to fuel artistic imagination, emphasizing the discovery of "various battles, and rapid actions of figures" within these natural stimuli (da Vinci & McCurdy, 1958). These accounts suggest a tangible connection between pareidolia and artistic inspiration, aligning with the study that

demonstrated how ambiguous visual cues can prime subsequent creative endeavors (X. Wu et al., 2019).

The essence of pareidolia isn't just celebrated in artistic anecdotes—it's also central to psychological assessments. The renowned Rorschach Test, wherein participants interpret abstract inkblots, hinges on principles mirroring pareidolia, while probing the individual's creativity (Gregory, 2000). Recent studies on pareidolia primarily focused on face detection mechanisms (Hong et al., 2013; J. Lee, 2016; Liu et al., 2014a). This line of work mostly probes *constrained pareidolia*, which implies a predetermined number of perceptual states in the stimulus (e.g. face vs. no-face). A more naturalistic approach consists in the study of *unconstrained pareidolia*, which implies an open-ended interpretation of stimuli, allowing for a multitude of perceptual outcomes beyond the simple binary categorizations. Following this approach, recent exploration into creativity's link to pareidolia, using natural scenery images (Diana et al., 2021) and statistical fractal images (Bellemare-Pepin et al., 2022), has expanded in recent years. These research efforts demonstrate a positive relationship between creativity, as measured by Divergent Thinking Tasks (Guilford, 1967; Olson et al., 2021) and specific questionnaires (B. Nelson & Rawlings, 2009a), and the occurrence and diversity of pareidolic perceptions. More specifically, highly creative individuals report more pareidolic experiences in the same image and across a wider range of stimulus complexity levels, as indexed by the fractal dimension (Bellemare-Pepin et al., 2022). This result is consistent with findings that such individuals often exhibit faster perceptual switching in visual illusions like the Necker Cube and Spinning Dancer (Blake & Palmisano, 2021).

DIVERGENT THINKING

Conceptual solution space



DIVERGENT PERCEPTION

Perceptual solution space

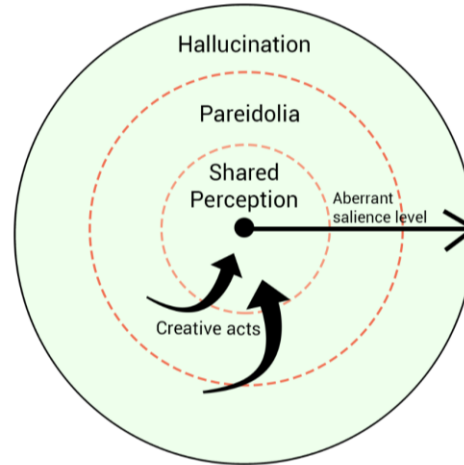


Figure 1.2. A comparative illustration of Divergent Thinking and Divergent Perception. The "Conceptual Solution Space" denotes the realm in which ideas are formulated, while the "Perceptual Solution Space" indicates the area where perceptions arise. The outward-moving arrow represents the divergent property. In the context of divergent thinking, this corresponds to increased remoteness of association, while for divergent perception, it relates to increased granularity of predictions and complexity in the sensory input (aberrant salience). Conversely, the inward-moving arrows signify the restructuring of the solution space, either by transforming remote associations into closer ones or by incorporating phenomena like pareidolia and hallucinations into the collective perceptual domain through creative acts.

As pareidolia and divergent thinking converge in their capacity to perceive manifold interpretations from a unique context, I propose *divergent perception* as the perceptual counterpart to divergent thinking (see **Fig. 1.2**). Divergent thinking, epitomized by the Alternate Uses Test (AUT), operates within a *Conceptual Solution Space*, and involves identifying multiple potential solutions to a given problem. For instance, in the AUT, participants are asked to think of as many uses as possible for a common object, such as a brick, leading to diverse answers ranging from a doorstep to an improvised weight for exercising. Analogously, divergent perception functions within a *Perceptual Solution Space*, implying the identification of varied interpretations (solutions) to one ambiguous image (sensory problem).

The AUT assesses divergent thinking using three criteria: fluency, flexibility, and originality (Almeida et al., 2008; Guilford, 1967). Here, fluency is the quantity of distinct responses, flexibility

is the range of contexts from which ideas are generated, and originality captures their innovative nature. Mapping this framework onto pareidolia, a parallel is observed: fluency becomes the multitude of distinct patterns one discerns in a given image, and flexibility reflects the variety of stimuli one can interpret. Recent findings suggest that those with higher creative tendencies both perceive patterns in a greater array of stimuli and see more varied interpretations in individual images (Bellemare-Pepin et al., 2022). Measuring the originality of pareidolic percepts poses a notable challenge, mirroring the difficulties encountered in assessing originality within divergent thinking tasks (Plucker et al., 2011; Runco et al., 2016). Several potential methods for evaluating pareidolic percept originality exist, ranging from expert ratings and comparisons with extensive databases to determining semantic distances between perceived contents. It's posited that the degree of originality in pareidolic percepts could serve as an indicator of the depth of creativity inherent to such perceptual experiences. Paralleling approaches that utilize latent semantic analysis in divergent thinking (Johnson et al., 2022; Olson et al., 2021), one approach to evaluating this originality could involve measuring the semantic distance between various pareidolic interpretations. For instance, more unconventional or novel perceptions might catalyze enhanced creative idea generation, facilitated by remote associations and auto-fictional narratives. To further elucidate the nexus between divergent perception and creativity, a promising approach consists in supplementing behavioral and electrophysiological data with qualitative insights from naturalistic pareidolia experiments.

Evolutionary perspective on pareidolic perception

The evolutionary approach to understanding creativity, as outlined by (Dietrich & Haider, 2015), offers unique insights into the phenomenon of pareidolia. This perspective draws parallels between creative cognition and natural selection processes, emphasizing the roles of variation and selection. In a Darwinian framework, variation is typically blind, unfolding without regard to the subsequent selection process. In the context of idea generation, variations become "partially

sighted", meaning that the generation process is influenced by certain selection criteria. In this scenario, the brain simulates, or emulates, a range of potential solutions, selecting them based on their alignment with predefined criteria. A high degree of sightedness signifies a structured exploration within established parameters, while a low degree, or "blindness", denotes a more random and unforeseeable exploration.

Extending this to pareidolia, our brain appears to function akin to an evolutionary algorithm (Dietrich & Haider, 2015; Todd et al., 2012). It navigates the vast problem space of sensory data, introducing perceptual variations via gestalt mechanisms. Attention, with its dual orientation—both internal and external—serves as the selection mechanism. It amplifies specific perceptions based on alignment between internal memory traces and prevailing external stimuli. Thus, pareidolia can be conceptualized as the outcome of the brain's systematic approach to attributing meaning to ambiguous sensory inputs via processes of variation and selection.

Consistently, the Honing Theory of Creativity (Gabora, 2017) suggests that creativity emerges from initial chaotic states (representing variation) which subsequently undergo cognitive restructuring (analogous to selection). It posits that "the creative mind uses psychological entropy (arousal provoking uncertainty) to detect and track concepts in states of potentiality, consider them from different perspectives [...] until psychological entropy reaches an acceptable level" (Gabora, 2017). In pareidolic perception, this chaotic state is prompted by ambiguous stimuli, producing high granularity of predictions and consequent increase in prediction errors. Pattern recognition, or the emergence of pareidolia, reflects the subsequent cognitive restructuring.

Drawing from the variation-selection approach, Bilder & Knudsen (2014) propose a model of creative thinking anchored in systems biology. They posit that blind variation functions on the "perception-action cycle" at a frequency close to 3 Hz, roughly the time required to compare a stimulus to expectations. They differentiate between systematic and stochastic variations: the former involves cognitive control (executive-control networks), while the latter deactivates

cognitive control and solicits the default mode networks. This classification resonates with Dietrich (2004) demarcation between spontaneous and deliberate creativity. The spontaneous mode, requiring fewer cognitive resources, often culminates in intuitive "Aha!" moments and facilitates broader, albeit partially sighted, explorations into solution spaces. In contrast, the deliberate mode entails an in-depth, conscious exploration, utilizing substantial cognitive resources, especially when navigating unknown domains. Much like the spontaneous mode of creativity, pareidolia can manifest suddenly, where ambiguous stimuli are intuitively and almost instantaneously translated into recognizable patterns. Conversely, in its deliberate form, pareidolia represents a more conscious and effortful unraveling of patterns from ambiguous stimuli. This suggests that spontaneous pareidolia may predominantly engage bottom-up processing, while deliberate pareidolia likely necessitates increased top-down cognitive control. Both manifestations underscore the brain's multifaceted strategies in extracting meaning from ambiguous visual stimuli.

In sum, the brain processes sensory data by applying mechanisms of variation and selection, seeking meaning from ambiguous stimuli. Central to this function is the role of salience, which prioritizes specific patterns or ideas from a wide array of sensory inputs. In the following section, I will further explore how salience is crucial in understanding the connections between creativity and pareidolia, extending its relevance to other domains such as psychedelic states, psychosis, and artificial intelligence.

Aberrant salience as shared process of creativity and pareidolia

Central to pareidolia is the concept of aberrant salience, which refers to an altered state of attention wherein the usual suppression of perceived 'irrelevant' or familiar information is disrupted (Kapur, 2003; Kapur et al., 2005). This state, characterized by a lack of latent inhibition, allows for a flood of information to enter the brain, a condition often described as "leaky" attention.

In this state, individuals inadvertently register "irrelevant" details (Carson et al., 2003; Mendelsohn & Griswold, 1964; Rawlings, 1985; D. Zabelina et al., 2016), broadening the scope of sensory interpretation. This compromised inhibitory function might enable the rise of pareidolic perceptions through concomitant complexification of sensory data and increase in top-down modulations. Consistently, (Brugger, 2001) describes a continuum ranging from detection of real patterns on one end, to hyper-creative interpretation of patterns in noise at the other end, suggesting that (1) creativity relies on the favoring of 'remote' over 'close' associations (Mednick, 1962) and (2) noisy (unpredictability) sensory environments are conducive to the perception of 'remote' associations.

Aberrant salience in psychotic symptoms

Aberrant salience, as well as pareidolia have been related to positive symptoms of schizophrenia, such as delusional thinking, paranoia and hallucinations (Belayachi et al., 2015; Vercammen et al., 2008; Yokoi et al., 2014). Latent inhibition has been associated with both psychosis (Kapur, 2003) and creativity (Carson et al., 2003), while other studies reported positive correlation between positive schizotypic symptoms and creativity (Batey & Furnham, 2008; Brugger, 2001; Burch et al., 2006; O'Reilly et al., 2001), and between creativity, latent inhibition and psychopathology (Chirila & Feldman, 2012). Hence, the perceptual mechanism of aberrant salience may explain the relation between positive schizotypic symptoms and heightened creativity within the schizophrenic population. Brugger (2001) proposed that this readiness to perceptually connect unrelated objects and ideas is what "most closely links creativity to psychosis". Pareidolia and altered inhibitory processes are known to be widely experienced perceptual mechanisms, suggesting that this link between aberrant salience, pareidolia and creativity, could generalize to individuals without schizophrenia. Consistently, weaker visual reality discrimination and increased pareidolia proneness are associated with hallucination-like experiences for non-clinical populations (Smailes et al., 2021).

Aberrant salience in psychedelic states

While I have highlighted the interplay of aberrant salience in psychotic symptoms, a rich avenue of exploration lies in the phenomenology of psychedelic states. These states, notably, offer glimpses into the mechanisms underpinning the convergence of creativity and perception. Psychedelics, as seen in various studies, not only amplify creativity (Costa, 2023; Gandy et al., 2022; Hartogsohn, 2018), but also instigate unique perceptual phenomena. Yet, the precise mechanisms that enhance creative capacities during psychedelic experiences, and the role of altered perception in this enhancement remain elusive (Sessa, 2008).

One key effect of psychedelic experience is the amplification of meaning (Carhart-Harris et al., 2014; Fischer & Landon, 1972; Kaelen et al., 2015; Preller et al., 2017; Preller & Vollenweider, 2016), which may account for sharpening of creativity (Hartogsohn, 2018). Psychedelics are thought to work the way electronic amplifiers do, hence magnifying the gain of whatever sensation reaches perception. The modulation of information gain by psychedelics leads to the emergence of unique representations and acute sensory processing (Geyer & Vollenweider, 2008; Vollenweider & Geyer, 2001). This results in an altered assignment of meaning to stimuli that would typically be perceived as neutral (R. Griffiths et al., 2008; R. R. Griffiths et al., 2006; Hartogsohn, 2018; Kaelen et al., 2015; Pahnke & Richards, 1966; Preller et al., 2017), an observation that draws parallels with pareidolic perceptions. Thus, the inherently ambiguous nature of perception during psychedelic experiences is thought to foster hyper-associative modes of cognition, a potential determinant of creative idea generation (Girn et al., 2020). Building on this notion, research using DeepDream in a virtual reality environment demonstrated that simulated altered perceptual phenomenology enhances cognitive flexibility (Rastelli et al., 2022).

Three pivotal features of the psychedelic state have been identified as potential creativity boosters: the increased complexity of experience, meaning amplification, and the sense of

interconnectedness with the environment (Sessa, 2008). I suggest that the intrinsic richness and complexity of the psychedelic experience might stem from shifts in primary attentional and salience processes (Millière et al., 2018). These processes can account for the rich perceptual experiences and the resulting pareidolic and hallucinatory episodes. Such experiences, in turn, feed into the enhanced sense of interconnectedness and meaning, given that they blur the boundaries of internal and external perception. This approach further bolsters the argument that models of embodied cognition might account for creativity.

Moving to brain dynamics, the entropic brain theory links the qualities of psychedelic experiences to distinctive brain signal properties (Carhart-Harris, 2018a; Carhart-Harris et al., 2014; Carhart-Harris & Friston, 2019). This theory suggests that psychedelic states are marked by increased brain entropy, aligning with the Integrated Information Theory which views psychedelics as broadening potential mental states (Gallimore, 2015). Brain entropy corresponds to the quantification of the diversity of possible neural states, suggesting a higher capacity for novel thought patterns and enhanced cognitive flexibility during psychedelic experiences. Empirical evidence reveals an expanded range of potential brain states during psychedelic influence (Tagliazucchi et al., 2014), heightened signal entropy and diversity (Lebedev et al., 2016; Schartner et al., 2017; Tagliazucchi et al., 2014; Timmermann et al., 2019, 2023; Viol et al., 2017, 2019), and facilitated state transitions stemming from a flattening of the brain's energy landscape (Singleton et al., 2022). In other words, this is like the brain finding new paths and connections more freely, as if the usual barriers or rules guiding its activity are temporarily lowered. Coherently, psychedelic state has been characterized by its super-criticality (Atasoy et al., 2017; Atasoy, Vohryzek, et al., 2018; Carhart-Harris & Friston, 2019; Gervais et al., 2023; Girn et al., 2023), which is thought to favor flexibility and perturbation over preservation (exploration over exploitation). Further elaboration by Pink-Hashkes et al. (2017) proposes that this elevated entropy may stem from overly detailed sensory predictions (i.e. higher granularity), resulting in

amplified prediction errors. This notion parallels the belief that aberrant salience underpins certain phenomenological aspects shared by psychedelic and psychotic symptoms, such as illusory percepts and hyper-associative mode of thinking, which might rise from increased brain entropy (Carhart-Harris, 2018a; Carhart-Harris et al., 2014). This hyper-associative thinking, while contributing to the richness of psychedelic experiences, acts as a double-edged sword by enhancing creativity on one side and mirroring the disorganized thought patterns seen in psychosis on the other. Interestingly, higher levels of entropy have been associated with different measures of creativity using both EEG (Mölle et al., 1999; Ueno et al., 2015) and fMRI (Shi et al., 2019). The results showed increased entropy in brain regions responsible for inhibitory control, reinforcing the idea that inhibitory and attentional processes are involved in creative idea generation.

In conclusion, aberrant salience during psychedelic experiences might be key in understanding perceptual mechanisms facilitating creative idea generation. Enhanced sensory landscapes might be conducive to idea generation, albeit without necessarily refining the evaluation of these ideas. Drawing from this, Baggott (2015) postulates that aberrant bottom-up processes might be fundamental to creativity. "This seemingly paradoxical effect by which error could improve cognition is reminiscent of the large literature in psychology showing that disagreement can improve decision-making" (Baggott, 2015). Essentially, the altered perception inherent in psychedelic and psychotic states, driven by aberrant salience and increased short-term prediction errors, could partly account for the heightened creativity observed in these conditions.

Aberrant salience in artificial neural networks

Another way to relate altered attentional processes with creativity is by observing behaviors of artificial neural networks (ANN). I already explained how ANN requires sensory data (as a way to perceive the world) in order to express any form of "creative" behavior, such as the

way DeepDream, or Latent diffusion models (LDM) generate hallucinatory-like figures by over-emphasizing the presence of pre-learned categories in new data. In other words, neural networks can identify patterns even in random noise and are able to 'see' objects or faces in ambiguous stimuli (Nguyen et al., 2016). This shows that pareidolia-like phenomena can be reproduced artificially and suggests an overlap between the cognitive mechanisms leading to pareidolia and those used in modern AI algorithms.

For instance, when DeepDream gets a new image as input (sensory input), instead of waiting until the last layer of neurons to identify with the highest confidence what is the content of the image, predictions are allowed from early stages and propagated to subsequent layers until an output is reached (generated image/perception). This mechanism of emphasizing the emergence of meaning within local structures - instead of only predicting the global structure - corresponds to an increase in the granularity of predictions. This mechanism is only possible when the salience threshold gets lower, hence leading to states of aberrant salience, and then to pareidolia (Keshavan & Sudarshan, 2017). If this perceptual mechanism is central to creative generation, this may explain why artists often report creating by building on pareidolic perceptions emerging from natural complex objects (da Vinci & McCurdy, 1958; Gamberini, 2002). The use of LDMs, which are able to generate state-of-the-art images based on text descriptions, also exemplify pareidolic-like processes in machines. To do so, a denoising autoencoder is applied iteratively on a noise image to unveil the structure hidden in the randomness based on a fit with the internal representations of the model. Hence, by filtering noise with patterns associated with semantic knowledge, any type of (pareidolic) structure can be sculpted from randomness. This exemplifies how diffusion models benefit from "sensory ambiguity" in the process of generating new visual structures, hence mimicking the formation of pareidolia and hallucination in humans, while providing new tools for creative exploration in humans.

Artificial networks and biological networks both create knowledge by developing complex models of the world, similar to how the human brain works (Thaler, 2016). This analogy extends to (artificial) creativity, which is suggested to stem from system perturbations that are characteristic of psychopathologies such as schizophrenia and bipolar disorder and may be facilitated by noise induction. Thaler (2016) proposes that creativity occurs through a cyclical process consisting of two phases: (1) cognitive incapacitation, where incubated confabulatory thoughts are generated (increased noise), and (2) synaptic calm, where these incubated thoughts are recognized as valuable and reinforce themselves (decreased noise).

When viewed within a pareidolic framework, ambiguous stimuli may act as a trigger, leading to the momentary emergence of confabulatory thoughts. As a result, pareidolic perceptions are thought to correspond to these confabulatory concepts, suggesting that pareidolia may represent the first phase of the creative process. It has been suggested that internally perturbed neural networks serve as an "ideational engine" by producing potential new ideas through the emergence of false memories (Thaler, 2016). Pareidolic perceptions result from top-down modulations, leading to an exogenous perception of internal models, which are linked to and inseparable from personal memories. Hence, it is suggested that pareidolic perceptions, which are the result of interactions between sensory noise and internal models, are similar to false memories but experienced through perception.

"The qualities of the unpredictable will serve as guiding principles in the process of perceptual emergence." *Unknown, 2022* - found near a river, engraved on a silver bark.

Aberrant salience in creative cognition

From an empirical standpoint, various evidence showed that disinhibition is a mechanism that could lead to idea generation and creative problem solving (Carson et al., 2003; Radel et al., 2015), while creative individuals have proven to often lack inhibition in both behavior and cognition

(Camarda et al., 2018; Dorfman et al., 2008; Kwiatkowski et al., 1999). Jarosz et al., (2012) demonstrated that alcohol, a strong disinhibitor, facilitates creativity through ideational fluency. Furthermore, Dimkov (2018) suggested that aberrant salience (i.e. reduced filtering of irrelevant information), provides "the building material for creative ideas". As a complementary perspective, (D. L. Zabelina & Robinson, 2010) found that creative achievement and divergent thinking were not directly related to cognitive (dis)inhibition, but rather to flexible modulations of cognitive control. This supports the theory of creativity that distinguishes between the exploration (disinhibition; divergent) and selection (inhibition; convergent) phases (Simonton, 2010a, 2011; Sowden et al., 2015).

This aberrant salience phenomenon parallels the evolutionary perspective on creativity. With a lowered threshold for what is perceived as salient, individuals absorb more information, leading to more detailed, albeit less accurate, predictions. Consequently, there is an increase in prediction error, fostering a more diverse exploration within the same problem space. Interestingly, sensory noise is considered as an essential driving force for the perceptual switching mechanism and by extension, to the emergence of meaning (Chen et al., 2023). Viewed through a fractal lens, every perceptible medium, like sound or light waves, can present endless variations depending on the precision of measurement. It is suggested that creative individuals enhance their sensory perception by voluntarily increasing the prediction error when faced with complex stimuli. This deliberate increase facilitates a process of "meaning amplification". Essentially, to counteract the challenges of heightened prediction error, creative minds amplify meaning to clarify ambiguities. Consistently, it has been shown that the reward effect in the appreciation of aesthetic work might come from the transition from a state of uncertainty to a state of increased predictability (Van De Cruys & Wagemans, 2011).

Taken together, this body of knowledge points to sensory disinhibition as a key predictor of pareidolic percepts. In the context of sensory overload, the natural tendency of the brain to

make sense of input leads to an increase in top-down modulations. Internal representations are then fitted to sensory noise, resulting in increased propensity to remote associations and pareidolic perception. I propose that aberrant salience, through the facilitation of remote associations, constitutes a fundamental ingredient of both pareidolia and creative ideation.

Brain Networks Dynamics Underlying Pareidolia and Creativity

This section explores the association between divergent perception and the (co)activation of brain networks responsible for attentional processes. Initially, I will examine studies on brain networks involved in psychedelic experiences and creative cognition. Subsequently, these insights will be integrated into an overview of the brain network dynamics underlying divergent perception.

Brain networks under psychedelics

Recent research sheds light on the distinct neural alterations during the peak effects of psychedelics. A pivotal study by Stoliker et al., (2023) reveals that under LSD, the salience network's inhibitory connectivity to the default mode network (DMN) switches to an excitatory mode. Concurrently, the inhibitory link from the DMN to the Dorsal-Attentional Network (DAN) weakens. This attenuation of the DMN-DAN anti-correlation is thought to contribute to the blurring of self and external world boundaries, a hallmark of psychedelic experiences. These LSD-induced network dynamics resonate with earlier findings in psychosis. For instance, aberrant coupling was observed across the DMN, Task-Positive Network (TPN), and Salience Network in individuals predisposed to psychosis Wotruba et al., (2014). This was interpreted as a confusion between internally and externally focused states, leading to cognitive dysfunction.

Psychedelics also appear to enhance bottom-up processing, reflected by an increased prevalence of states dominated by somato-motor and Ventral Attention Network (VAN)/salience networks (Singleton et al., 2021). The relaxation of high-level cognitive priors under psychedelics

implies a freer flow of bottom-up information, especially from interoceptive sources (Carhart-Harris & Friston, 2019). Furthermore, visual and auditory hallucinations under psychedelics have been linked to specific network interactions. Abnormal DMN coupling with the visual network during visual hallucinations (Shine et al., 2015) and reduced antagonism between the DMN and the language network correlating with auditory hallucinations (H. Geng et al., 2020) have been reported. These insights into brain network modulation under psychedelics underscore their influence on ambiguous sensory processing, particularly relevant to pareidolia, where enhanced creative cognition is likely facilitated by these altered states of perception.

Brain networks of creativity

Neuroscientific evidence, primarily from neuroimaging studies, underscores the relationship between creativity and the dynamic cooperation of typically opposing brain networks. Key studies highlight cognitive flexibility, evidenced by the synergistic interaction of the DMN, Executive Control Networks (ECNs), and Salience Network. This interplay is crucial for creative thought (Beaty et al., 2015; Chrysikou, 2019; Jung, 2013). Visual creativity, for instance, has been linked to increased coupling between DMN and ECN regions, especially observed in professional artists (De Pisapia et al., 2016). The interconnectivity within and between the DMN and the Fronto-Parietal Network (FPN), responsible for executive control, is also pivotal in both verbal and visual creativity (Zhu et al., 2017). These studies collectively demonstrate a pattern of decreased within-network connectivity and enhanced between-network connectivity, reinforcing the cooperative nature of the default and executive networks in creative endeavors.

In alignment with the dual-process model of creativity, which delineates generative (variation) and evaluation (selection) phases (Chrysikou, 2019; Lopata et al., 2022); recent findings delving into the temporal dynamics of network recruitment during creative idea generation identified increased DMN activity in the early variation phase, shifting to heightened ECN activity in the later selection phase (Lloyd-Cox et al., 2022). Here, enhanced bottom-up attention

facilitates idea generation, while increased top-down attention aids the evaluation phase (Beaty et al., 2016; Ellamil et al., 2012; Kleinmintz et al., 2019). Additionally, Tabatabaeian & Jennings (2023) propose a novel framework for creative cognition, emphasizing dynamic attentional mechanisms. They suggest conceptualizing attention along two axes: from bottom-up to top-down (source axis), and from internal to external (target axis). This model posits that internal and external attention interact during creative cognition, a theory supported by evidence showing simultaneous engagement of networks associated with both attention types during creative tasks (Beaty et al., 2018; K. C. R. Fox et al., 2015; K. C. R. Fox & Christoff, 2018). The model distinguishes between bottom-up attention with internal (e.g. intrusive thoughts) and external (e.g. unexpected stimuli) targets. Such bottom-up attention is pivotal in the idea generation phase, while both internal and external top-down attention are instrumental in the evaluation phase. The dynamic interplay between DMN, FPN, and sensory cortices, modulated by the SN, facilitates the creative process by continuously prioritizing salient events (internal or external). Interestingly, on the other hand, individuals with Autism Spectrum Disorder, which exhibit lower fluency and flexibility in creativity tests (Pennisi et al., 2021), often exhibit a salience network with diminished entropy and a dominant presence of lower-frequency components. This particularity might explain their characteristic inflexible behavior and difficulty to deal with uncertainty.

Brain networks of divergent perception

The interplay of neural networks observed during altered states induced by psychedelics and during creative processes offers a promising avenue to probe into the neural scaffolding that supports unconstrained pareidolia. These findings highlight the complex interplay between attentional processes subtended by different brain networks, and the potential for alterations in these dynamics to impact both perception and creativity.

Research indicates that heightened activity within the DMN, known for its specialization in introspective and self-referential thought, can predispose an individual to hallucinations by

allowing intra-network regions to overly influence ongoing visual streams (Shine et al., 2015). During overt hallucinatory episodes, a marked decrease in DAN activity coincides with an increase in DMN activity. This shift in network dynamics also reveals a surge in capacities such as salience monitoring and attention shifting, which are central to the VAN. Furthermore, these visual attention-related functional networks, including the DMN, VAN, and DAN, play a pivotal role in visual misperception (Shine et al., 2011, 2015). This flexible pattern of activity mirrors that found in the initial phases of the creative process, where the DMN coactivates with networks overseeing sensory input (e.g., visual networks) or guiding the distribution of attentional resources (e.g., salience network and VAN).

I suggest that during divergent perception, the salience network concurrently emphasizes internal and external bottom-up information, while coordinating information exchange between DMN and FPN, akin to both psychedelic and creative states. Hence, pareidolia emerges from the brain's heightened emphasis on internal representations during moments of sensory uncertainty, leveraging the DMN's augmented connectivity with sensory and attentional networks to sculpt meaningful percepts. In other words, pareidolia showcases the brain's adaptability in weaving together disparate informational threads to form unified percepts. The intricate relationships between involuntary and executively controlled perceptual processes and their contribution to creative thought is visualized in the schematic representation provided in **Figure 1.3**.

The increased flexibility of brain network dynamics during both creativity and altered perception aligns with the critical brain hypothesis, which states that brain networks operate close to a critical point, i.e. in the vicinity of phase transition (O'Byrne & Jerbi, 2022a). This zone is characterized as a transitional state teetering between order and chaos, optimizing the versatility of the state repertoire. It has been demonstrated that criticality of brain functioning enables more efficient information processing while maintaining a balance between adaptability and order (Shew & Plenz, 2013). Studies on psychedelics revealed a broadening of the energy landscape,

predominance of excitation over inhibition (E/I) and increases of the brain's signal diversity, a state of so-called supercriticality (O'Byrne & Jerbi, 2022a). Hence, divergent perception might maximize the E/I ratio through increased sensory streams of ambiguous information and/or reduction of inhibitory processes. I hypothesize that pareidolia is a perceptual phenomenon that allows the brain to actively sample unpredictable sensory data, resulting in an increase in short-term entropy or brain complexity. This phenomenon seeks to optimize model updating, which enhances their ability to incorporate as much sensory information as possible, ultimately reducing long-term uncertainty. In other words, memories and active internal schemas are used to meaningfully link distant sensory information through the creation of a situated, embodied and self-referential narratives.

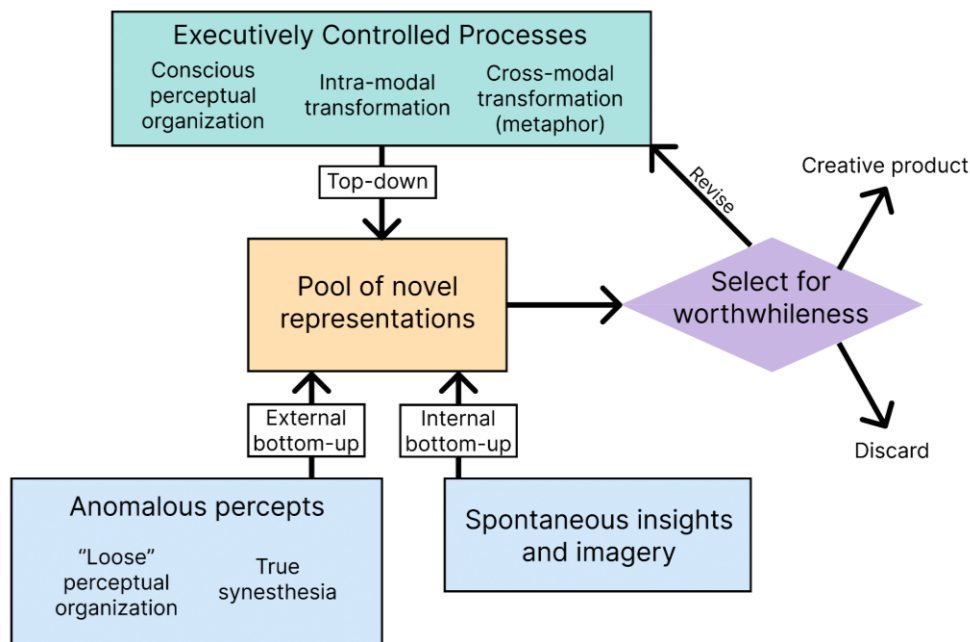


Figure 1.3. Contribution of involuntary and executively controlled perceptual processes in creative thought (Adapted from Flower and Garbin, 1989). The figure depicts the interplay between cognitive processes and perceptual representations in creativity. "Anomalous Percepts," being external bottom-up signaling, are the brain's interpretations of ambiguous or unfamiliar external stimuli. "Spontaneous Insight & Imagery" represents internal bottom-up signaling, mediated by the DMN, wherein ideas or images emerge without conscious effort. The transition to "Executively Controlled Processes" shows how these perceptions and insights are consciously organized, refined, or transformed. The "Pool of Novel Representations" can be seen as the brain's playground for pareidolia – a space where ambiguous stimuli are interpreted and mixed together, leading to the generation of novel ideas. These representations are then assessed for their value, leading to their selection, revision, or discard, culminating in the formation of a "Creative Product."

Pareidolia as a source of creative ideation and emergent narratives

"Pareidolia is a creative act because it is not about seeing things for what they are but seeing things for what they could be" Heath & Ventura (2016)

The neuroscientific literature has long discussed the significance of remote associations in the creative process (Gough, 1976; Gruszka & Necka, 2002; Mednick, 1962; Sassenberg et al., 2017). Those with a heightened aptitude for remote associations might use divergent perception as a source of semantic divergence. Here I propose a mechanism by which divergent perception gives rise to creative ideation: emergent narratives.

In the realm of semiotic theories, the phenomenon of pareidolia offers a unique parallel to the way personal narratives are formed and shared. Just as we creatively represent ourselves through self-referential narratives (Milthorp, 2003), pareidolia involves responding to stimuli as signs, even when their inherent semiotic objectives are ambiguous (Alexander, 2013). This "self-mistaking" can prompt innovative cognitive pathways, fostering new interpretations and associations (Alexander, 2013). These pathways embody our quest to find meaning, reflecting how we navigate through the limitations and possibilities of the world. I suggest that such self-mistaking perceptions can lead to the emergence of narratives or, in broader semiotic terms, novel purposeful behaviors. Congruently, self-referential narratives have been suggested as foundational to creative behaviors (Milthorp, 2003). These insights underscore the profound ties between biosemiotics, self-referential narratives, divergent perception, and creativity.

Future paths for the empirical investigation of divergent perception through pareidolia

This manuscript intends to provide insights into the perceptual mechanisms underlying creative idea generation. Drawing from these insights, I propose several empirical investigations to explore the relationship between inter-individual differences in divergent perception and the

generation of creative ideas. In the following section, I describe six aspects of the pareidolic phenomenon that can be leveraged to optimize experimental designs that probe creative behavior.

Stimulus properties affecting pareidolia

I first explained the intrinsic link that binds perception and creativity together, and suggested pareidolia as a type of perception that can be associated with the early phase of creative idea generation. It might further be questioned how pareidolia could be experimentally manipulated through systematic variations of stimulus properties.

Fractal dimension (FD) corresponds to the fractal scaling relationship between the patterns observed at different magnifications (Spehar et al., 2003). FD is a measure of self-similarity that can be computed on any image with the box-counting method (Li et al., 2006). Images of lower FD can be conceived as being less detailed, while images of higher FD are perceived as more detailed and inherently complex (Cutting & Garvin, 1987a; Gilden et al., 1993; Pentland, 1984). It means that in images of higher FD, there are higher probabilities of finding similar patterns at different scales.

Rogowitz & Voss (1990) initially explored the impact of FD on pareidolic perceptions using generative cloud images. Subsequent work revealed that images with lower FD led to more pareidolic perceptions (Taylor et al., 2017a), with a peak in pareidolia observed around an FD of 1.3 (A. Bies, Kikumoto, et al., 2016). This FD intriguingly correlates with aesthetic preferences (Aks & Sprott, 1996; Hagerhall et al., 2004a; Spehar et al., 2003; Taylor et al., 2005). Hence, the FD might influence the activation of specific neural networks responsible for aesthetic evaluation, suggesting a mechanistic link between the neural bases of pareidolia, aesthetic preferences, and creative interpretation. Recent systematic investigations have delved deeper into this relationship, using Divergent Thinking Tasks to more comprehensively evaluate the interplay between

creativity and pareidolia (Bellemare-Pepin et al., 2022; Diana et al., 2021). These studies encourage a more comprehensive exploration of stimulus attributes in modulating pareidolia. They also invite examining the relationship between neural and stimulus fractal properties, a dynamic potentially influenced by the presence or absence of pareidolia.

I propose that creative generation rooted in sensory experience (as opposed to mental simulations) can benefit from the inherent properties of sensory information, such as fractal dimension and self-organizing principles, similar to how stochastic resonance amplifies weak signals with noise induction (Gammaitoni et al., 2009; Moss, 2004). The top-down modulation of ambiguous information enables internal representations to interact with each other within emergent embodied perceptual content. The inherent complexity of the stimuli and the malleability of internal representations provide novel combinations of remote concepts through the emergence of new, seemingly unfamiliar percepts. Hence, prototypic internal representations can coexist within ambiguous sensory information and lead to new modes of interaction, highlighting the natural role of fractal noise in generating new ideas.

Multi-fractal images to stimulate pareidolia

Previous research has focused on quantifying the relationship between pareidolia and the (mono)fractal dimension of stimuli, yielding promising results in understanding how stimulus properties influence the propensity for pareidolia. This line of inquiry naturally extends to multifractality, a concept that underscores the complexity of signals whose fractal dimension varies across different scales or frequencies, highlighting varying degrees of self-similarity. The multifractal spectrum describes the distribution of the singularity strength (Hölder exponent) of a signal over a range of scales. This property is observed in many complex systems, such as turbulence in fluids (Meneveau & Sreenivasan, 1991), physiological signals like heart rate variability (Faini et al., 2021; Ivanov et al., 1999), and financial data (Bouchaud et al., 2000). By creating multifractal images, pareidolic perception can be investigated in relation to the distribution

of fractal dimensions within a single stimulus. It is possible that images with a particular range of fractal dimensions would more readily facilitate pareidolia than others. Furthermore, certain types of multifractal images might stimulate pareidolia more effectively than monofractal images.

Parallel versus sequential pareidolia

Future pareidolic investigations should emphasize discerning parallel from sequential pareidolia in their design frameworks. The former involves concurrently perceiving multiple interpretations within a stimulus, while the latter entails multiple non-coexistent perceptions. Stimuli with lower fractal dimensions may be more conducive to sequential pareidolia given that their pareidolic components occupy more visual space, making it challenging to perceive multiple images at once. In contrast, stimuli with higher fractal dimensions could foster parallel pareidolia. Leonardo da Vinci's observations underscored how multiple pareidolic interpretations can coexist, feeding into one another to form rich visual sceneries. If emergent narratives form a bridge between pareidolia and creativity, highly creative individuals might navigate parallel pareidolia more intuitively, weaving multifaceted narratives from overlapping perceptions.

Spontaneous versus deliberate pareidolia

Equally important for future research is the exploration of spontaneous versus deliberate pareidolia, two fundamentally different cognitive processes, initially brought forth to explain creativity (Dietrich, 2004, 2019a), that influence how individuals engage with and interpret ambiguous stimuli. Spontaneous pareidolia refers to the involuntary and instant recognition of patterns or meanings, while deliberate pareidolia is a conscious effort to seek out patterns or connections in sensory input. Understanding the interplay between these two forms could shed light on various cognitive and creative dynamics. For instance, it might be essential to explore whether highly creative individuals show a higher propensity for one type over the other or if they can switch between these modes more fluidly depending on the context. Additionally, investigating

how training or environmental factors influence the ability to engage in deliberate pareidolia could offer educational strategies to enhance creative thinking skills.

The semantic distance of pareidolic percepts

An emerging frontier in pareidolic research is the assessment of not only the quantity but also the originality of perceptions. Latent semantic analysis is increasingly recognized as a method to delve into creative capacities, primarily through semantic distance metrics. Semantic distance refers to the measure of how similar or dissimilar the meanings of two words or concepts are. It is generally computed using algorithms that analyze the relationships between words in large text corpora, based on their co-occurrence frequencies, contextual similarities, or positioning within a semantic network or vector space model. Specifically, the Divergent Association Task (Olson et al., 2021), which measures creativity through the semantic distance between word pairs, and the Divergent Semantic Integration (Johnson et al., 2022), evaluating divergent integration in consecutive sentences, both harness latent semantic analysis to gauge creativity. To assess perceptual originality, one approach could be to capture participants' descriptors for pareidolic perceptions and subject them to latent semantic analysis, thereby gauging semantic creativity. This method might illuminate how the semantic nuances of pareidolic perceptions could be fertile grounds for generating innovative ideas and unexpected narratives.

Comparing human and machine pareidolia

As seen in previous sections, artificial neural networks trained on large datasets are able to transform images based on their internal representations, a process that bears similarities with human pareidolia. Such models could also predict the content of images, even when it is highly ambiguous. While human pareidolia is deeply embedded in our cognitive and perceptual faculties, often influenced by past experiences, emotions, and cultural backgrounds, ANN pareidolia is rooted in purely statistical learning approaches. This distinction raises intriguing questions about

the nature of perception. Is the human tendency for pareidolia inherently more complex due to its integration with emotions and memories, or does it merely represent a more intricate pattern recognition system, akin to sophisticated ANN architectures? Further exploration in this domain could bridge gaps between cognitive neuroscience and machine learning, offering insights into how machines might be trained to mimic human-like creative perceptions. It would also be intriguing to investigate if exposing ANNs to more human-like learning experiences, such as sequential and contextual learning, could make their pareidolic interpretations more aligned with human perceptions.

Conclusion

In this perspective piece, I explored the profound connection between the perception of ambiguous stimuli and the genesis of creative ideas. I introduced *divergent perception* as the perceptual analogue to divergent thinking, which is predominantly linked with the exploration phase of the creative process. I proposed the *aberrant salience* mechanism to elucidate the common phenomenological experiences of altered perception found in both psychedelic states and psychotic episodes. Additionally, literature on brain networks related to psychedelics and creativity was synthesized to develop hypotheses regarding the neural networks underpinning divergent perception. Exploring the neural signatures linked to pareidolia and understanding how various stimulus attributes influence this phenomenon can also catalyze innovation in brain-computer interface (BCI) technology. Indeed, by manipulating these stimuli and their corresponding perceptions in real-time, a new generation of BCIs may emerge, seamlessly integrating human cognition with technology and amplifying our ability to channel creative ideation. I offer this framework to steer forthcoming research in creative cognition, aiming to deepen comprehension of the interplay between creativity and divergent perception.

Processing visual ambiguity in fractal patterns: Pareidolia as a sign of creativity

Abstract

Creativity is a highly sought after and multifaceted skill. Unfortunately, we only have a loose grasp on its cognitive underpinnings. Empirical research typically probes creativity by estimating the potential for problem solving and novel idea generation, a process known as “divergent thinking”. Here, by contrast, we examine creativity through the lens of perceptual abilities. In particular, we ask whether creative individuals are better at perceiving recognizable forms in noisy or ambiguous stimuli, a phenomenon known as pareidolia. To this end, we designed a visual perception task in which 50 participants, with various levels of creativity, were presented with ambiguous stimuli and asked to identify as many recognizable forms as possible. The stimuli consisted of cloud-like images with various levels of complexity, which we controlled by manipulating fractal dimension (FD) and contrast level. We found that pareidolic perceptions arise more often and more rapidly in individuals who are more creative. Furthermore, the emergence of pareidolia in individuals with lower creativity scores was more restricted to images with a narrow range of FD values, suggesting a wider repertoire for perceptual abilities in creative individuals. Our findings suggest that pareidolia may be used as a perceptual proxy of idea generation abilities, a key component of creative behavior. In sum, we extend the established body of work on divergent thinking, by introducing divergent perception as a complementary manifestation of the creative mind. These findings expand our understanding of the perception-creation link and open new paths in studying creative behavior in humans.

Introduction

Creativity is a cornerstone of human evolution. It allows us to adapt to our environment and transform it. A widely accepted definition of creativity is the ability to produce work that is both novel (i.e., original, unexpected) and useful (i.e. adaptive given task constraints) (Sternberg & Lubart, 1998), though it has been argued that this definition does not capture the full breadth and multiple facets of creativity (Barbot et al., 2015; Dietrich, 2007; Fryer, 2012; Glăveanu, 2014). Additionally, although there have been many attempts to characterize the neural mechanisms underlying creativity (Dietrich, 2004; Jung et al., 2009; Simonton, 2010b; Wiggins, 2006), no consensus has yet emerged (Dietrich & Kanso, 2010; Sawyer, 2011). To date, most of the empirical research on creativity has focused on the concept of divergent thinking (DT; (Guilford, 1950; Runco et al., 2016; Weisberg, 2006), defined as the ability to generate multiple solutions to an open-ended problem (Guilford, 1950, 1967). The most widely used measure of creativity, the Torrance Tests of Creative Thinking (TTCT), consists mostly of DT tests (Kim, 2006). Two major problems arise when claiming that DT tests measure creativity per se (Dietrich, 2018, 2019b). First, it has been argued that the opposite – convergent thinking – can also produce creative ideas (Simonton, 2015b). Second, DT is a compound construct, which gathers multiple facets and mental processes within a single measure (Ward et al., 1999). These problems invite caution when approaching creativity as a monolithic entity (Dietrich, 2019b) and beckon for complementary ways of operationalizing this multifaceted concept. Many accounts of creativity focus on cognitive processes, i.e. thinking differently. In this paper, we instead examine whether highly creative individuals differ in their perceptual processes, i.e. seeing differently.

It has recently been proposed that our ability to create depends heavily on our ability to perceive and model the external world (Heath & Ventura, 2016b). Indeed, creative individuals seem to process external sensory stimuli differently (Flowers & Garbin, 1989), in that they will tend to connect unrelated elements together more easily. Accordingly, researchers have begun to

investigate creativity through the lens of embodied cognition (Malinin, 2019), which views action and perception as complementary. This approach emphasizes exploration and interactions with the physical environment as essential prerequisites for the emergence of cognition and therefore of creativity, attributing to attention the creative role of diversifying the field of experience and perceptual contents (D'Angelo, 2019). A study on creative experience under the effect of psychedelics also distinguishes between creative performances, which can be recorded, and creative experiences, which are subjective and anchored in perception (Fischer & Scheib, 1971). This distinction between creative action (performance) and creative perception (experience) points to the importance of studying the phenomenology of creativity (C. B. Nelson, 2005) complementarily to classical measures involving the production of creative artifacts. Finally, it has been suggested that creativity might emerge through *confused perception* (such as Beethoven's deafness), *malfunctioning perception* (such as psychotic symptoms), and *intentional perception* (expertise and use of analogical thinking) (Pereira & Tschimmel, 2012). These cases of altered perception result from an increase in noise/uncertainty in the sensory signal whether through degradation of receptors, in the case of deafness or blindness, or through increased prediction errors and reduced latent inhibition, as it is the case in psychotic symptoms or psychedelic experiences. Together, these studies suggest that high-creative individuals have perceptual abilities that differ from low-creative individuals, and more specifically, that they might process ambiguous stimuli differently. However, to our knowledge, this has not yet been systematically investigated.

A natural approach to exploring inter-individual variability in processing ambiguous images is to exploit pareidolia, which is the experience of seeing meaningful patterns or connections in random stimuli, a fundamental aspect of human perception (Fyfe et al., 2008). Interestingly, pareidolia is thought to be an adaptive skill, as it may have helped early hominids to detect threats in complex sensory environments (Barrett, 2000; Meschiari, 2009). At the root of pareidolia is a

concept called aberrant salience, which corresponds to an altered attentional state leading to a failed suppression of irrelevant or familiar information (Kapur, 2003; Kapur et al., 2005). This decrease of latent inhibition may facilitate the emergence of pareidolic perceptions through concomitant complexification of sensory data and increases in top-down modulations. Pareidolia proneness is associated with schizophrenia symptoms, such as delusional thinking, paranoia, and hallucinations (Belayachi et al., 2015; Vercammen et al., 2008; Yokoi et al., 2014). In a non-clinical population, a common example of pareidolia is the perception of meaningful objects in clouds. Clouds are complex visual stimuli which exhibit inherently unpredictable structures, making them ambiguous by nature. This ambiguity can be perceived in one of two ways. First, the brain can perceive it as noise with no relevant information and attribute the label cloud to the perceived image. In the second pareidolic instance, the brain makes an association between random features of the cloud and a known object, resulting in the perception of a meaningful object in noise such as a cat or a heart. However, it is important to note that this perceived cat or heart does not perfectly match any one previously perceived exemplar, but rather, it creatively emerges from the interaction of the semantic concept with the details of the fractal image. In short, "Pareidolia is a creative act because it is not about seeing things for what they are but seeing things for what they could be" (Heath & Ventura, 2016b).

Pareidolia has mostly been studied in the context of face detection (Hong et al., 2013; J. Lee, 2016; Liu et al., 2014a), although more recent studies have also examined natural scenery images (Diana et al., 2021) and generative stimuli (A. J. Bies et al., 2016; Rogowitz & Voss, 1990a; Taylor et al., 2017a). Crucially, the empirical relation between creativity and pareidolia has received very little attention. A rare exception is an interesting study by Diana et al., (2021), which suggests that fluency on a DT task significantly predicts fluency and originality in a Divergent Pareidolia Task. Pareidolia can be seen as a perceptual counterpart of DT, in that it relies on the possibility of finding multiple solutions within a single problem space. The problem to be solved

emerges from the ambiguity in the stimulus, and pareidolic perceptions are the multiple solutions to that problem. While DT probes creative thinking in the context of semantic problems resolved through conceptual expansion, divergent perception probes creative perception in the context of sensory problems resolved through pattern recognition. Pareidolia and creative thinking thus share the common fundamental process of relying on divergent processes to generate new ideas or percepts. In the context of DT, idea generation is measured in terms of fluency, flexibility, and originality (Almeida et al., 2008; Guilford, 1967). In divergent perception, percept generation can likewise be measured in terms of pareidolic fluency (finding multiple percepts in a unique stimulus) and flexibility (finding at least one percept in a wide range of stimuli).

Previous research indicates that the emergence of pareidolia depends on image properties including contrast and fractality. These properties are therefore likely to moderate the proposed relation between the observer's creativity and their tendency to experience pareidolia. Image fractality can be quantified by its fractal dimension (*FD*), a measure of the signal's self-similarity when observed at different magnifications. One of the first studies to assess the effect of *FD* on pareidolia reported a relation between the *FD* of generative cloud images and the prevalence of pareidolia (Rogowitz & Voss, 1990a). The authors presented four images simultaneously to participants and asked them to indicate the image in which a recognizable object was first detected. Although this method is useful to determine the *FD* that preferably elicits spontaneous pareidolia, it does not speak to the systematic relations between fractality and pareidolia. Moreover, no statistical analysis was conducted on this dataset. A second study (Taylor et al., 2017a) investigated the relation between pareidolia and *FD* by exposing 23 participants to a set of 24 images with *FD* ranging from 1.05 to 1.95. Participants were asked to report the number of percepts elicited by each stimulus. Results indicated that lower *FD* stimuli elicited significantly more pareidolic percepts. While this study has the advantage of systematically investigating the relation between *FD* and pareidolia, it is limited by a small sample size and a

small number of stimuli. In the same vein, Bies et al. (2016) demonstrated that object pareidolia is more diverse and occurs faster for *FD* values close to 1.3. However, the number of stimuli used in the experiment was limited to 4 per *FD*, for a total of 16, which may limit statistical inferences. Interestingly, the *FD* that tends to facilitate pareidolia ($FD = 1.3$) has also been associated with the perception of beauty and aesthetic preference (Aks & Sprott, 1996; Hagerhall et al., 2004b; Taylor et al., 2005), both in synthetic noise images and works of art (Viengkham & Spehar, 2018), suggesting that a stimulus with higher chance of triggering pareidolia might also be judged as more aesthetically appealing. Coherently, Taylor and Spehar (2016) developed a fluency model suggesting that mid-*FDs* (1.3-1.5) optimize both the observer's capacities of pattern recognition and the emergence of aesthetic experience. Individual differences between preferred patterns in a range of *FD* have been systematically investigated by Spehar et al. (2016), who report that 90% of individuals can be classified as either preferring low (20%), intermediate (50%) or high (20%) *FDs*, while no specific link between these profiles and creativity has been investigated. These individual differences in susceptibility to pareidolia across different *FDs* suggest that the modulation of image *FD* offers a means to experimentally manipulate pareidolia in a laboratory setting.

Here, we set out to investigate the link between pareidolic perception and creative experience, as well as the moderating role of situational factors. To this end, we developed a novel pareidolia paradigm where fifty participants with various levels of creativity viewed a wide range of synthetic cloud-like images. Importantly, we generated the stimuli by manipulation of fractal dimension and contrast and predicted that pareidolia would occur preferentially at intermediate *FD* levels (close to 1.3) consistently with previous research (A. J. Bies et al., 2016) and that higher contrast would facilitate pareidolia. In a first step, we sought to validate the presence of a relation between pareidolia and two key properties of the generated stimuli (*FD* and contrast). We then proceeded with our main objectives and hypothesized that creativity would be

positively correlated with pareidolia. In terms of moderation, we expected that *FD* and contrast level would moderate the relation between creativity and pareidolia. Specifically, we predicted that differences between low- and high-creatives would be amplified for optimal settings of *FD* and contrast.

Creativity was primarily measured using the Experience of Creativity Questionnaire (ECQ; Nelson & Rawlings, 2009), which focuses on the phenomenological dimension of creativity and is designed to measure individual differences in the intensity of the creative experience as well as the depth of immersion when engaging in creative processes. This approach to assessing creativity is appealing for two main reasons: First, by being non-domain-specific, the ECQ can capture creativity irrespective of whether individuals engage in the production of creative artifacts or other classical artistic practices. Second, by focusing on the phenomenological aspect of the creative process, the ECQ captures the perceptual components of the creative experience, which according to our hypothesis, would correlate with pareidolia. This said, because the use of self-reported creativity measures has its limitations, we also administered a complementary creativity test that measures divergent thinking. For this, we used the recently proposed Divergent Association Task (DAT; Olson et al., 2021), which requires the participant to find words that are the most semantically distant from one another. The associated creativity score is then computed automatically by estimating the mean semantic distance between the proposed words. Importantly, this study (Olson et al., 2021) has shown that DAT correlates with performance on two widely used creativity measures (the Alternative Uses Task and the Bridge-the-Associative-Gap Task). This was confirmed in two different datasets, and a high test-retest reliability was observed ($r = 0.73$; see their Table 4 for a list of correlations between DAT and different dimensions of divergent thinking). Although DAT does not measure exactly divergent thinking in its standard definition, it is thought to assess the efficiency/flexibility of the associative network

(Olson et al., 2021). As a result, the use of the ECQ and DAT in the present study allows us to probe the relation between self-reported creativity, divergent thinking, and pareidolia.

Results

All participants viewed 360 visual fractal stimuli and were instructed to identify as many percepts as possible in each image during the 8-second presentation. The stimuli consisted of 3 levels of contrast and 12 levels of fractal dimensions ranging from 0.8 to 1.9 (**Fig.2.1**). Reaction times were measured as the latency of the button press indicating the emergence of the first pareidolic percept. We conducted an image-based analysis of reported pareidolia to address the potential issue of response bias. If the responses of the participants (i.e. pareidolia occurrence and number of percepts) were random and unrelated to pareidolia occurrence, we'd expect the mean pareidolia responses for the stimuli to be similar across all stimuli. Both for pareidolia occurrences and for the number of objects variables, we found that the response distributions across subjects were significantly different from the distributions of random behavioral responses (**Fig. S2.2**). These results indicate that the distribution of the original data significantly differs from that of randomly generated behavioral responses.

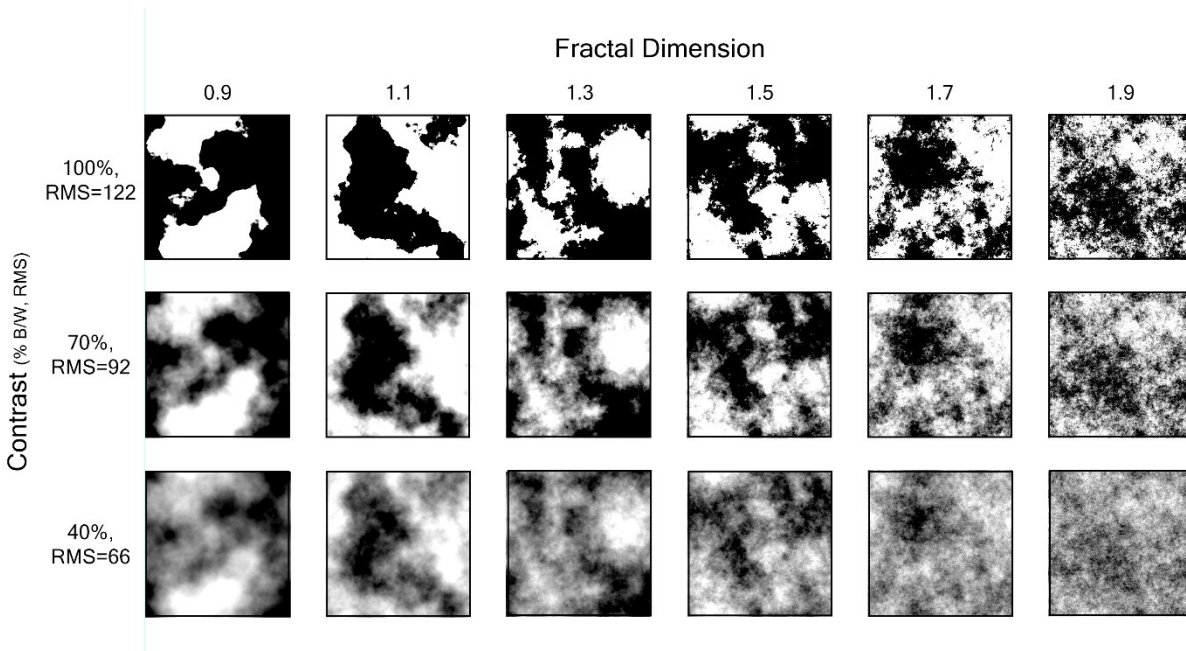


Figure 2.1. Stimuli generated with Fractional Brownian Motion algorithm. The X-axis represents the three levels of contrast, ranging from full black and white (left), to 20% of black and 20% of white (right). The Y-axis represents the fractal dimension of stimuli, ranging from 0.9 to 1.9.

Effect of stimulus fractal dimension on pareidolia

Considering the hypothesis that intermediate *FDs* (around 1.3) might facilitate pareidolia and given that the scatterplots showed clear inverted U-shapes, regressions were computed to model both the linear and the quadratic effect of *FD* on each of the four dependent variables (see **Fig. 2.2.**). We found significant quadratic relations between *FD* and pareidolia occurrences (*Par*), $R^2 = .91$, $F(2,9) = 43.51$, $p < .001$, and number of objects (*N_obj*), $R^2 = .86$, $F(2,9) = 28.25$, $p < .001$, while the linear trend explained more variance than the quadratic trend for reaction time (*RT*) and spontaneous pareidolia (*Spont_par*). These results indicate that low- to mid-*FDs* are associated with increased pareidolia, mid-*FDs* yield a higher number of pareidolic percepts, and low-*FDs* facilitate rapid and spontaneous pareidolia.

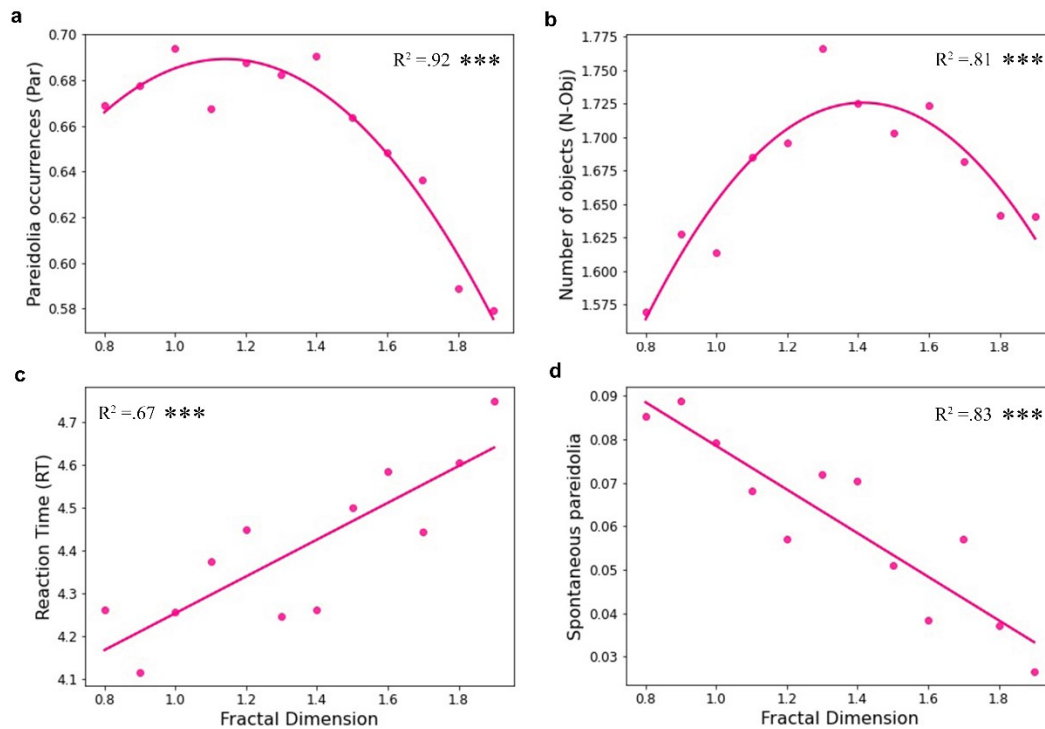


Figure 2.2. Pareidolia as a function of fractal dimension (FD). (a) Pareidolia occurrences (*Par*) as a function of *FD*. (b) Number of perceived objects for pareidolia trials as a function of *FD*. (c) Time before first pareidolic percept as function of *FD*. (d) Proportion of pareidolia trials with reaction time shorter than 2 seconds. R^2 corresponds to the adjusted coefficient of determination in the corresponding regression model. *** $p < .001$.

Effect of image contrast on pareidolia

To investigate the effect of contrast on pareidolia, we ran a repeated-measure ANOVA with a Greenhouse-Geisser correction on each of the four DVs. We found a statistically significant effect of contrast on the occurrence of pareidolia (*Par*), $F(1.65, 74.03) = 49.5$, $p < .001$, the number of pareidolic percepts (*N_obj*), $F(1.5, 67.67) = 81.94$, $p < .001$, reaction time (*RT*), $F(1.8, 75.51) = 11.46$, $p < .001$ and spontaneous pareidolia (*Spont_par*) $F(1.61, 72.63) = 8.78$, $p < .001$. Post hoc tests using the Bonferroni correction revealed that all contrast levels differed significantly ($p < .001$) for *Par* and *N_obj*, while for *RT* and *Spont_par*, only high-contrast images differed significantly from mid-contrast (*RT*: $p < .01$, *Spont_par*: $p < .05$) and low-contrast (both p

< .01). These results indicate that high-contrast images facilitate both the flexibility and the fluency of pareidolia, as well as the speed of its emergence.

Relation between creativity measures and pareidolia

To test our main hypothesis that high-creatives experience increased pareidolia we computed the Spearman correlations between creativity (both self-reported and based on divergent thinking) and properties of pareidolic experience across participants. Spearman correlations were used because our measures of number of objects and spontaneous pareidolia were not normally distributed. More specifically, we assessed pairwise correlations between two measures of creativity (*DAT* and *Crea_pheno*) and four measures of pareidolia (*Par*, *N_obj*, *Reaction Time* and *Spont_par*), and controlled for multiple correlations using the False Discovery Rate (FDR). Sample sizes for this correlational analysis ranged from 42 to 50. **Figure 2.3** shows that *Crea_pheno* was significantly correlated with the four measures of pareidolia: *Par* ($r(49) = 0.55, p < .01$), *N_obj* ($r(49) = 0.47, p < .05$), *RT* ($r(49) = -.36, p < .05$), *spont_par* ($r(49) = .5, p < .01$), while *DAT* scores were correlated with *par* ($r(41) = .5, p < .01$), *N_obj* ($r(41) = .37, p < .05$), *RT* ($r(41) = .35, p < .05$) and with *Crea_pheno* ($r(41) = .33, p < .05$).

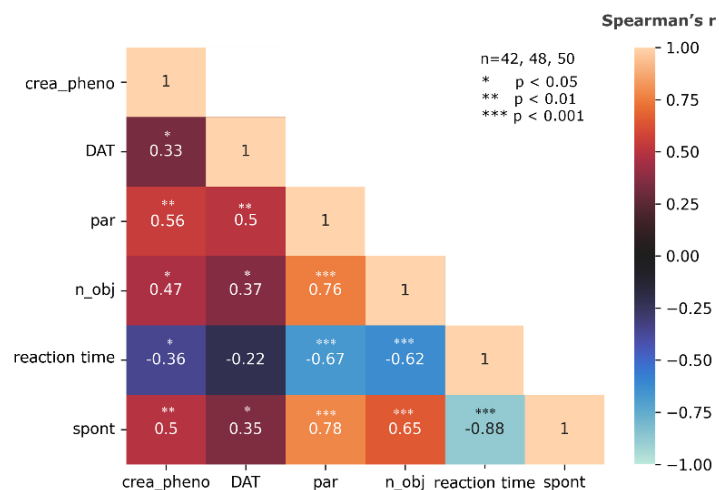


Figure 2.3. Correlation matrix of creativity measures and pareidolia. Par: Pareidolia occurrences, N_obj: Number of objects, reaction time: Reaction Time, spont_par: Spontaneous pareidolia, crea_pheno: Creative phenomenology, DAT: Divergent Association Task. All analyses were performed using maximum sample size ($n = 42$ for DAT, $n = 48$ for RT and Spont_par, and $n = 50$ for the rest). Significance levels were * $p < .05$; ** $p < .01$; *** $p < .001$. See Figure S2.4. for normality tests on these variables.

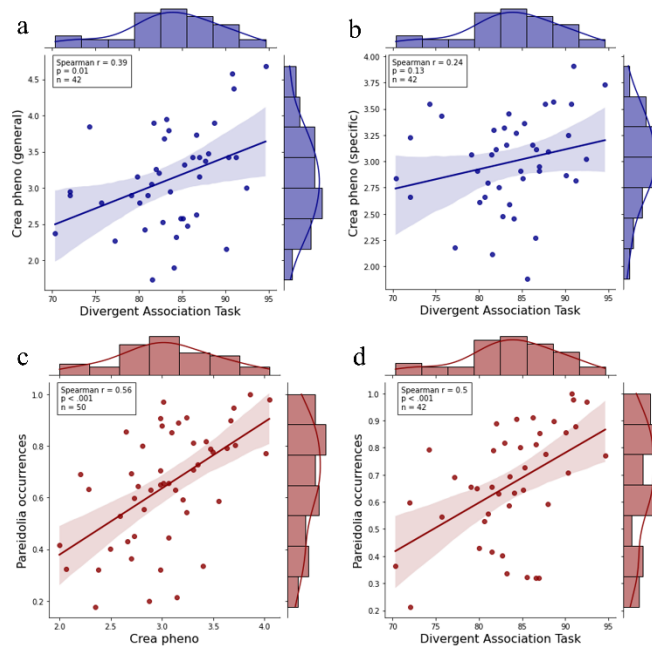


Figure 2.4. Spearman correlations between self-reported creativity, divergent association and pareidolia occurrences (*Par*). (a) Significant correlation between the general dimension of *Crea_pheno* and DAT. (b) Non-significant correlation between the specific dimension of *Crea_pheno* and DAT. (c) Significant correlation between *Crea_pheno* and pareidolia occurrences. (d) Significant correlation between DAT and pareidolia occurrences. Pareidolia scores are averaged across all trials.

To get a better understanding of the correlation between DAT (our measure of divergent thinking) and *Crea_pheno* (self-reported metric of creativity), we performed further correlation analysis between DAT scores and each of the two sub-dimensions of the *Crea_pheno* test: the first is related to one specific creative experience the participant identifies with (*Crea pheno specific*), and the second reflects the assessment of creative processes in a broader sense (*Crea pheno general*). The results are shown in **Figure 2.4a-b**. Interestingly, this analysis revealed that divergent thinking (i.e. DAT) was significantly correlated with the general dimension of *Crea_pheno* ($r(41) = .39, p < .05$) but not with the sub-component that assesses a specific creative experience ($r(41) = .24, p = .13$).

Together, these results support the hypothesis that creative individuals are more prone to experience pareidolia. The main statistical models presented in the subsequent sections are built using *Crea_pheno* because this measure exhibited the strongest correlation with pareidolia and

was available for all 50 participants (the DAT scores were only available in the 42 participants who were able to participate in the follow-up data collection). This said, the observed correlations between both types of creativity metrics and pareidolia will be useful for our interpretation and discussion. Results of the GLMM using DAT as a dependent variable are provided in supplementary material; **Table S2.1**).

Interaction effects of creativity, fractal dimension and contrast on pareidolia

We ran generalized linear mixed-effect models (GLMMs) that modelled the moderation effects of contrast and *FD* on creativity in predicting pareidolia occurrences (*Par*), number of objects (*N_obj*) and reaction time (*RT*). A quadratic term (FD^2) for both fixed and random effects of *FD* was included in the model in order to account for its nonlinear relation with pareidolia. Contrast was only considered in the fixed effect structure, as it has been recommended that random variables must have more than 12 levels (T. S. Clark & Linzer, 2015). The final model included all possible two-way interactions between creativity, *FD* and contrast, as well as their three-way interaction. We ran the GLMMs with all the subjects, as well as without subjects with scores higher than 3 SDs above the mean. We report the former case, while both cases result in the same significant effects.

The GLMM results in **Table 2.1** and **Figure 2.5** show that both *FD* ($p = .004$) and contrast ($p = .004$) interact significantly with creativity in predicting pareidolia occurrence, while the three-way interaction between *FD*, contrast and creativity was also significant. The two-way interactions validate the hypothesis that both *FD* and *contrast* moderate the effect of creativity on pareidolia, while the significant effect of *Crea_pheno* alone reveals that creativity predicts pareidolia at average level of *FD* and at high-contrast. The three-way interaction demonstrates that for high-contrast images, differences between low- and high-creatives are smaller for mid-*FD*s and larger for images of low- and high-*FD*s in predicting pareidolia.

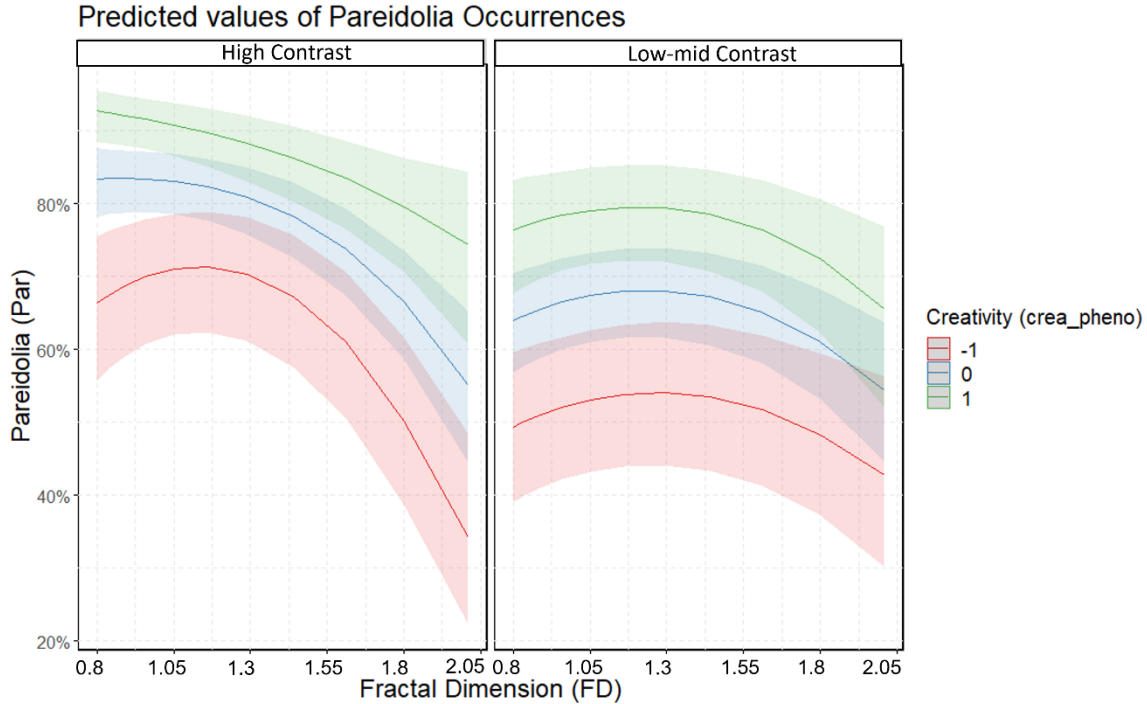


Figure 2.5. Predicted probabilities of the interaction between *FD*, Contrast and Creativity on pareidolia occurrences. Statistical values are in Table 2.1.

For the GLMM predicting N_{obj} , the moderation of stimulus properties on the relation between creativity and N_{obj} was not significant. Thus, a model only containing the main effects was adopted. We found significant fixed effects for the two moderator variables, FD ($p < 0.001$), FD^2 ($p < 0.001$), and $contrast$ ($p < 0.001$), as well as for $Crea_pheno$ ($p < 0.001$) (see **Table. 2.2**). We conducted a third GLMM that predicts reaction time (RT). This revealed significant fixed effects of $Crea_pheno$, FD and $Contrast$, and two-way interactions between $contrast$ and FD ($p < .001$) and between $contrast$ and $Crea_pheno$ (see **Table. 2.3**). The two interactions revealed that differences in RTs between high- vs. low-mid contrast were enhanced for low-FDs ($FD \times Contrast$) and high-creatives ($Contrast \times Creativity$), indicating that high-contrast images increase the probability of shorter reaction time especially for images with lower fractal dimension and individuals with high creativity scores. Note that no GLMM was built to predict spontaneous

pareidolia (*Spont_par*) since this variable was on the participant's level rather than on the observation's level.

| Fixed effects | Estimate | Std. Error | z value | p-value |
|--|----------|------------|---------|------------|
| (Intercept) | 1.57 | 0.19 | 8.50 | < 0.001*** |
| <i>FD</i> | 0.35 | 0.40 | 0.87 | 0.38 |
| <i>FD</i> ² | -1.2 | 0.35 | -3.44 | < 0.001*** |
| Contrast | -0.98 | 0.11 | -8.97 | < 0.001*** |
| Creativity | 1.11 | 0.19 | 5.92 | < 0.001*** |
| <i>FD</i> * Creativity | -1.21 | 0.42 | -2.88 | 0.004** |
| <i>FD</i> ² * Creativity | 0.94 | 0.36 | 2.6 | 0.009** |
| <i>FD</i> * Contrast | 0.45 | 0.44 | 1.43 | 0.31 |
| <i>FD</i> ² * Contrast | 0.29 | 0.38 | 0.77 | 0.44 |
| Contrast * Creativity | -0.33 | 0.12 | -2.86 | 0.004* |
| <i>FD</i> * Creativity * Contrast | 1.22 | 0.46 | 2.63 | 0.009** |
| <i>FD</i> ² * Creativity * Contrast | -1.02 | 0.40 | -2.57 | 0.01* |

Table 2.1. Moderation effect of *FD* and Contrast on Creativity in predicting Pareidolia (*Par*). Number of participants = 50, number of trials = 360, total $n = 18,000$. * $p < .05$; ** $p < .01$; *** $p < .001$.

| Fixed effects | Estimate | Std. Error | z value | p-value |
|------------------------|----------|------------|---------|------------|
| (Intercept) | -0.07 | 0.09 | -0.81 | 0.42 |
| <i>FD</i> | 0.90 | 0.18 | 5.04 | < 0.001*** |
| <i>FD</i> ² | -0.82 | 0.16 | -4.99 | < 0.001*** |
| Contrast | -0.33 | 0.02 | -16.92 | < 0.001*** |
| Creativity | 0.35 | 0.07 | 4.75 | < 0.001*** |

Table 2.2. Main effects of *FD*, Contrast and Creativity in predicting Number of Objects (*N_obj*). Number of participants = 50, number of trials = 360, total $n = 11,618$. * $p < .05$; ** $p < .01$; *** $p < .001$.

| Fixed effects | Estimate | Std. Error | t value | p-value |
|-----------------------------------|----------|------------|---------|------------|
| (Intercept) | 1.38 | 0.03 | 53.67 | < 0.001*** |
| <i>FD</i> | 0.15 | 0.23 | 6.55 | < 0.001*** |
| Contrast | 0.10 | 0.02 | 6.14 | < 0.001*** |
| Creativity | -0.1 | 0.03 | -3.72 | < 0.001*** |
| <i>FD</i> * Creativity | 0.02 | 0.02 | 0.89 | 0.37 |
| <i>FD</i> * Contrast | -0.08 | 0.03 | -3.21 | 0.001** |
| Contrast * Creativity | 0.04 | 0.02 | 2.05 | 0.04* |
| <i>FD</i> * Creativity * Contrast | -0.01 | 0.03 | -0.45 | 0.65 |

Table 2.3. Moderation of *FD* and Contrast on Creativity in predicting Reaction Time (RT).
Number of participants = 48, number of trials = 360, total $n = 9,557$. * $p < .05$; ** $p < .01$; *** $p < .001$.

We also conducted post-hoc Spearman correlation analyses to predict pareidolia occurrence (*Par*) from creativity scores at each level of *FD* and for the two categories of *contrast*. False Discovery Rate (FDR) correction for multiple correlations was applied. As shown in **Table 2.4**, for high-contrast images, our results show a larger effect size (Spearman Rho values) of *crea_pheno* for low- and high-*FD* in predicting pareidolia occurrence, indicating that the difference between low- and high-creatives is smaller for mid-*FD*s. For low-to-mid-contrast images, the trend is less clearly defined.

| <i>Par/FD</i> | 0.8 | 0.9 | 1 | 1.1 | 1.2 | 1.3 | 1.4 | 1.5 | 1.6 | 1.7 | 1.8 | 1.9 |
|---------------------|---------|---------|---------|---------|--------|---------|--------|---------|---------|---------|---------|---------|
| High contrast | 0.58*** | 0.53*** | 0.51*** | 0.50*** | 0.43** | 0.41** | 0.35* | 0.47*** | 0.44** | 0.46** | 0.50*** | 0.56*** |
| Low-to-mid-contrast | 0.50*** | 0.50*** | 0.56*** | 0.53*** | 0.45** | 0.55*** | 0.42** | 0.50*** | 0.51*** | 0.49*** | 0.45** | 0.31* |

Table 2.4. Spearman correlations for each Fractal Dimension (*FD*) to predict pareidolia from creativity scores.
Corrected p-values: * $p < .05$; ** $p < .01$; *** $p < .001$. $n = 50$ for each regression

Discussion

In this study, we investigated the relation between creativity and divergent perception. To do so, we implemented a novel pareidolia task in which participants were asked to identify recognizable forms in cloud-like images with different levels of fractality and contrast.

Typically, creativity is investigated by estimating the potential for creative problem solving and novel idea generation, a process known as divergent thinking. Here, in an important departure from previous work, we introduce divergent perception as a novel cognitive marker and predictor of creativity. Our results show that the perception of objects in ambiguous fractal stimuli (i.e. pareidolia) occurs more often and more rapidly in creative individuals. More specifically, linear mixed-effect modelling revealed that high-creative individuals are more flexible (wider range of optimal *FDs*), fluent (higher number of percepts) and faster in experiencing pareidolia. We also found that the association between creativity and pareidolia is stronger for high-contrast images with either low- or high-*FD*. Taken together, these results suggest that divergent perception captures a key cognitive feature of creativity, complementing established findings on divergent thinking. These results may have several future applications, in which pareidolic performance may be considered as a practical and easy-to-implement index of creativity or possibly a metric to monitor in the context of creativity training. In the following we discuss our main observations reported in light of previous work.

Pareidolia depends on image contrast and fractal dimension

Quadratic regression analyses revealed that low- to mid-*FDs* maximize occurrences of pareidolia across trials, while mid-range *FDs* promote higher numbers of percepts during trials of pareidolia. This last result is congruent with (A. J. Bies et al., 2016) who reported enhanced pareidolia in images with *FD* around 1.3. Consistently, quadratic regression analysis on reaction time indicates that pareidolia arises faster in low-*FDs*. Hence, pareidolia seems to be generally

facilitated by stimuli of lower levels of inherent complexity, consistently with previous findings (Rogowitz & Voss, 1990a; Taylor et al., 2017a), while mid-*FD* images facilitate the experience of multiple pareidolic percepts. Our results showed that higher levels of contrast are associated with increased pareidolia occurrence and number of perceived objects, as well as shorter reaction time. This effect is consistent with the figure-ground segregation principle of Gestalt theory, which explains that as contrast increases, so does the perceptual saliency of what is perceived as the object compared to what is identified as the background (Wagemans, Elder, et al., 2012). In the case of the pareidolia task, high contrast images seem to facilitate dissociation between black and white structures, leading to increased figure-ground segregation.

Higher creativity is associated with higher propensity to pareidolia

Our findings support the hypothesis that creativity is correlated with the propensity to pareidolia. In particular, the correlation analysis (**Fig. 2.3**) revealed that pareidolia occurrence is correlated both with phenomenological creativity and with divergent thinking abilities, measured via the Experience of Creativity Questionnaire (ECQ) and Divergent Association Task (DAT) respectively. These results support the view that creativity, measured with two complementary tools, is predictive of pareidolia during perception of fractal visual noise. Because of its complex and multifaceted nature, the breadth of human creativity cannot be fully captured in a single measure. Indeed, none of the available tests and assessment tools is optimal, and using a combination of metrics, each sensitive to distinct aspects of creativity, is recommended.

The GLMM results further demonstrated the significant fixed effect of creativity on the occurrence of pareidolia, the number of pareidolic percepts and reaction time, indicating with more confidence that creative individuals experience pareidolia more often (for different stimuli), more rapidly, and that they perceive higher number of percepts when pareidolia occurs. These findings are in line with studies on bistable perception demonstrating that self-reported creative individuals are able to reverse the percept significantly more often (Bergum & Bergum, 1979; Klintman, 1984;

Wernery, 2013), which requires the capacity to inhibit one percept over another. The role of (dis)inhibitory processes in creativity is not well established, and conflicting results indicate that both inhibitory (Benedek et al., 2012) and disinhibitory (Radel et al., 2015) processes might participate in the emergence of creative behaviour. Other studies point to the role of cognitive flexibility in creative ideation (de Dreu et al., 2011; Nijstad et al., 2010), while future studies are still required to investigate the relation between these processes and pareidolia.

Only very few studies have investigated the connections between pareidolia and creativity. One recent study (Wu et al., 2019) measured the impact of perceiving ambiguous stimuli on subsequent creative outcomes. Their results show that participants who passively looked at ambiguous figures, compared to non-ambiguous figures, scored higher on fluency, flexibility and originality in a subsequent Alternative Uses Task, and on creativity in a story generation task, thereby suggesting that processing ambiguous stimuli could have a beneficial priming effect on creative processes. Another recent study demonstrated that performances on both free association and divergent thinking tasks were predictive of pareidolic fluency and originality (Diana et al., 2021), also pointing to a functional role of pareidolia in creativity. With the present study, we incorporated a parametric manipulation of image complexity and showed that pareidolia relates to creativity, while this relation varies in function of the stimulus properties.

Higher creatives experience pareidolia across a larger repertoire of stimulus properties.

Correlation analyses revealed specific patterns of relation between creativity and pareidolia depending on the contrast level and the fractal dimension of the images. Analyzing high-contrast images, which previous analyses have shown to generally facilitate pareidolia more than low-mid-contrast images, we found that creativity predicts pareidolia specifically for low- and high-*FD* images. Two conclusions emerge from this result. First, it indicates that high-creatives seem to be more flexible in the way they integrate ambiguous information, as reflected by their

ability to experience pareidolia in a wider range of *FDs*. Since divergent perception skills of high-creatives are less dependent on the physical properties of the stimulus, this would probably reflect a greater capacity to voluntarily produce the pareidolic effect, even under less favorable stimulation conditions. Their ease to experience pareidolia in high-*FDs* images is coherent with preliminary results showing that self-reported high-creative individuals prefer looking at images with higher *FD* (Richards, 2001), which seems to have been the case for Jackson Pollock, whose paintings show increasing *FD* throughout his lifetime (Schiestl et al., 1999). The ability of creative individuals to detect multiple percepts more easily in ambiguous visual stimuli might result from a tendency to depart from the propensity to automatize perception toward a single, most predictable percept. Even though automatization of perception might facilitate behavioral efficiency in most of our daily tasks, the present findings suggest that creative individuals might rely on defusing these perceptual habits to maximize novelty seeking and idea generation.

Second, our results suggest that mid-*FDs* (around 1.3) may facilitate pareidolia, especially for low-creative individuals. This effect is further illustrated by the significant quadratic relationship between *FD* and pareidolia only for the low-creative group (see **Figure. S2.1**). These findings complement previous studies (Rogowitz & Voss, 1990a; Taylor et al., 2017a) that showed a facilitation of pareidolia for images of *FD* 1.3, by indicating that this effect may be more predominant for low-creative individuals. Given that images of *FD* 1.3 have also been associated with perception of beauty (Spehar et al., 2003), the present results suggest that stimuli perceived as aesthetic concomitantly facilitate the emergence of pareidolic percepts. This view is in line with theories of embodied cognition which posit that aesthetic quality is not a property of the stimulus, but an emergent phenomenon derived from the interaction between brain and stimulus (Roddy & Furlong, 2014).

Spontaneous and deliberate pareidolia

The difference in reaction times favoring high-creatives leads to the hypothesis that low- and high-creatives may rely on different perceptual strategies. One neuroscientific framework that may help to understand the mechanisms involved in pareidolia is the model proposed by Dietrich (2018), which suggests a distinction between deliberate and spontaneous modes of creativity. The deliberate mode implies a conscious process of trial-and-error, which recruits a large amount of cognitive and attentional resources, possibly involving top-down brain mechanisms. The spontaneous mode, on the other hand, implies an unconscious process leading to what is reported as insights and results from effortless attention and possibly bottom-up brain processes. This duality of intentional and spontaneous modes in creative behavior may also be linked to the concept of "flipflop thinking", i.e. alternating between greater focus and greater mind wandering (D. Zabelina et al., 2016).

We specifically tested the hypothesis that creative individuals are more prone to experience spontaneous pareidolia, which we defined as the ratio of the number of trials with *RTs* below 2 seconds to the total number of trials where pareidolia was reported. Our findings revealed a significant positive correlation between this metric of spontaneous pareidolia and creativity. Applied to the perspective of divergent perception, spontaneous pareidolia would correspond to the emergence of percepts in a context of low cognitive load, possibly as the result of an implicit resolution of confusion (Shen et al., 2016). This particularity of effortlessness associated with spontaneous creativity suggests that participants with higher spontaneous pareidolia might engage in the task with an effortless mode of attention. On the contrary, low-creative individuals may have more heavily relied on a deliberate mode of pareidolia, which implies a trial-and-error search process and higher cognitive load.

Divergent perception

Aside from proposing a functional link between creativity and perception of ambiguous stimuli, this study introduced a newly designed pareidolia task as a measure of divergent perception. We may think of the idea of divergent perception as the perceptual counterpart of divergent thinking. Hence, without having a direct “productive” outcome, pareidolia enables to account for a phenomenon of multiple coexisting solutions within a same problem space, as it is the case with classical divergent thinking tasks such as the Alternative Uses Task (AUT). The present study showed that creative individuals, as measured by two different metrics of creativity, have higher levels of fluency (number of objects) and flexibility (range of fractal dimensions) when performing a visual pareidolia task.

One might ask whether the perceptual processes investigated with a pareidolia task could merely be interpreted as imagination? A pareidolia task allows for divergent perception, which may overlap with processes generally involved in imagination, but is more specific to the case of finding multiple alternative solutions (here constructing multiple percepts) to a problem, as in divergent thinking. Arguably, creativity and imagination are intrinsically related and different types of imagination might not promote equally the emergence of creative idea generation. Several authors have drawn distinctions between categories of imagination, such as distinguishing between bottom-up and top-down imagination (Vyshedskiy, 2019), or between mental imagery, novel-combinatorial (counterfactual), altered state and phenomenology-based imagination (Abraham, 2016). Interestingly, pareidolia seems to encompass different categories of imagination, in that it relies both on the phenomenology associated with sensory experience and on the counterfactual process involved in “seeing” what is not objectively there based on prior experiences. Hence, we argue that divergent perception is a form of imagination that leads to idea generation through a balance between bottom-up and top-down processes.

Pareidolia as a source of creative ideation

The role of remote associations in creative processes has periodically appeared in the neuroscientific literature of creativity (Mednick, 1962; Sassenberg et al., 2017). Creative individuals, who are characterized by a propensity to perform remote associations, may use this skill at a perceptual level in order to more easily identify internal representations in ambiguous sensory information. Ambiguous stimuli would therefore constitute opportunities for a creative mind to apply top-down modulations that may result in conceptual expansion. By enriching sensory experience through a search for visual complexity, interactions with ambiguous stimuli afford the opportunity to resolve sensory dissonance with active top-down modulation. These top-down modulations allow the integration of sensory information into new conceptions and refined models. Hence, this adaptive strategy of making sense of (cognitively integrating) ambiguous sensory information gives rise to opportunities for constructing new models of the external world, based on the inherent complexity of stimuli. These new models are the very soil in which creativity plants its root and where new ideas can grow. Top-down modulations of ambiguous information enable internal representations to interact with each other within emergent perceptual content. Moreover, we might speculate that the inherent complexity of the stimuli enables the addition of uncertainty (natural noise) in the interaction between these internal representations. The malleability of internal representations, coupled with the inherent noise of sensory information, facilitates novel combinations of remote concepts, and the conjuration of seemingly non-familiar percepts. Hence, we suggest that pareidolia could be both a marker and a source of creative ideation.

Numerous artists anecdotally reported experiencing pareidolia as a source of inspiration in their creative work. As exposed in Gamboni, (2002) work *Potential Images*, Piero di Cosimo inspired his painting through looking at the sky, Novalis wrote about figures he saw in the clouds, and Chinese painter Sung Ti used the technique of looking at a dilapidated wall covered by a thin

piece of white silk: *“You gaze at it until you can see the ruins through the silk, its prominences, its levels, its zig-zags and its cleavages, storing them up in your mind, and fixing them in your eyes. Soon you will see men, birds, plants and trees, flying and moving among them. You may then ply your brush according to your fancy. (Gamboni, 2002)”*

Leonardo Da Vinci recommended in his *Treatise on Painting* to look at rock formations, stained surfaces, ashes and clouds, to get inspiration: *“Moreover, you can see various battles, and rapid actions of figures, strange expressions on faces, costumes, and an infinite number of things, which you can reduce to good, integrated form. (da Vinci & McCurdy, 1958)”* By looking at these natural sceneries, DaVinci demonstrates how prototypic internal representations can coexist within ambiguous sensory information and give rise to new modes of interactions, pointing to the natural role of fractal noise in the generation of new ideas. All these reports point to a functional link between pareidolia and creative inspiration, a link that is substantiated by the present study.

Conclusion

The present study is a first attempt to empirically link creativity and perceptual processes, using a pareidolia task. We showed that levels of creativity, whether measured by a questionnaire on phenomenological aspects of creative experience or through assessment of divergent thinking, significantly predict the occurrence of pareidolic experiences. We further identified systematic relations between pareidolia, creativity and the fractal dimension of the perceived visual stimuli. For high-contrast images, the propensity to experience pareidolia was higher in creative individuals specifically for low and high fractal dimensions. Taken together, these results indicate that (1) high levels of creativity are associated with enhanced pareidolia and (2) both fractal dimension and image contrast are key stimulus properties to manipulate when investigating pareidolic perception. These results also suggest that pareidolia could be a marker of idea generation and a predictor of creativity as it involves the perceptual ability of creating new ideas

from the integration of ambiguous stimuli. Our findings call for future research to expand our understanding of the neuro-cognitive mechanisms associated with multiple dimensions of creativity, as well as the efficient encoding of image statistics (Simoncelli & Olshausen, 2001). Future work might also benefit from integrating measures of visual imagery vividness (Salge et al., 2021) and content of the pareidolic percepts. The present results point towards the promise of probing creativity through the exploration of the neural dynamics associated with pareidolia. While a few studies have examined face pareidolia detection (Liu et al., 2014a; Rekow et al., 2022; Wardle et al., 2020)(38, 77, 78), none have used fractal visual stimuli with open-ended designs. Another promising avenue for further research, is designing methods to measure the properties of pareidolic percepts (e.g. richness, diversity) in order to strengthen the theoretical link between creativity and pareidolia.

Methods

Human participants

50 neurotypical individuals (19 females) between the ages of 19 and 35 ($M = 27.4$, $SD = 3.24$) took part in the experiment. All participants signed an informed consent form. Reaction time was not collected for two participants, leaving 48 participants for the analyses which required reaction times. The research project received ethics committee approval before all participants provided written informed consent to participate in this study.

Experimental protocol

In the first part of the experiment, 360 stimuli (3 levels of contrast and 12 levels of fractal dimension ranging from 0.8 to 1.9) were presented to each participant in a pseudo-random order. The participants faced the screen for the duration of the task and gave their answers using a standard keyboard. The images were of a size covering approximately 10 degrees of visual angle. The task of the participants was to detect the maximum number of percepts during the 8-second presentation of each stimulus. The participants had to press the spacebar when they perceived a

first figurative object in the stimulus. After each stimulus, they reported the total number of perceived objects (scale from 0 to 5-and-above). A block of 10 trials preceded the experiment so that the participants could get used to the task. Participants were told before the task that at the end of the experiment, images for which they report the highest number of objects will be presented to them again to assess the reported content. This procedure was deliberately implemented to reduce the chances that participants provide false responses during the test. During the experimental procedure, there was no mention of the term “creativity”, as we wanted to avoid putting any pressure on the participants to perform well on a “creativity test”. The participants were told that it was a study on perception, and that it could be seen as a game, similar to finding objects in the clouds and that there were no good or bad answers. The experimenter stayed with the participants during this test block in order to answer any questions. The experiment lasted about 60 minutes, divided into three blocks of twenty minutes, between which it was proposed to the participants to take a short break if desired.

Creativity assessment

The participants completed the Experience of Creativity Questionnaire (ECQ), a phenomenological measure of creativity, which is divided into two parts. The first part, which refers to a specific creative activity, comprises five subscales: power/pleasure, absorption, distinct experience, anxiety and clarity of preparation. The second part, reflecting the engagement with creative activities in general, is divided in three subscales: transformation, centrality of the experience, and transpersonal. The five subscales of the first part closely relate to flow-type experiences, which have been identified as a specific form of creativity (Dietrich, 2004). As a complementary measure to the ECQ, we chose a recently introduced behavioral measure of creativity, the Divergent Association Task (DAT), for which the data was collected in a follow-up study in 41 out of the 50 participants. Participants had to provide the ten most semantically distant words. Semantic distance between each pair of words was computed with GloVe (Pennington et

al., 2014) a freely available model which was pre-trained on the Common Crawl corpus, containing text from billions of web pages. Since the participants were French speakers, the data were collected in French. We tried using GloVe with a French database but found that a significant proportion of words were not recognized by the algorithm. Hence, the words were translated to English before computing the score. One of these participants was treated as an outlier as their score exceeded 3 SDs above the mean. The creativity tests were always administered after the pareidolia task, alongside a series of other tests (meditation, personality, flow state).

Stimulus design

Fractal dimension (*FD*) describes the fractal scaling relation between the patterns observed at different magnifications (Spehar et al., 2003). Many algorithms allow for the computation of fractal dimension (Lopes & Betrouni, 2009). Images of lower *FD* can be considered less detailed, while images of higher *FD* are more detailed and inherently complex (Cutting & Garvin, 1987a; Gilden et al., 1993; Pentland, 1984). Fractals themselves are characterized as either *exact* or *statistical*. Exact fractals exhibit a geometry that repeats itself exactly at different levels of magnification, while statistical fractals contain a certain degree of randomness within their structure, leading to partial similarities between different magnifications.

Statistical fractal images were generated using a $1/f$ spatial noise (Lennon, 2000a) based on the inverse discrete Fourier Transform (**Fig. 2.1**), allowing control over the *FD* of each image. The fractal dimension was derived from the spectral slope (*Beta*) of the distribution with the formula $FD = (Beta * 2 - 6) / 2$. Beta values ranged from -2.2 (\approx brown noise) to -1.1 (\approx pink noise) and corresponding *FD* values from 0.8 to 1.9. Variability in spectral slope between different images has also been demonstrated using natural images (Tolhurst et al., 1992). This algorithm allowed to generate images with autocorrelated structure and values following a gaussian distribution.

We generated a set of 360 images of size 512 by 512 pixels. The images were manipulated to create three distinct levels of contrast. At high contrast, half of all image pixels were set to black and the other half to white by thresholding the grayscale image at the mean luminance level, as in (Spehar et al., 2016). Two other contrast levels were generated by thresholding at 35% from each extreme of the spectrum for medium contrast (leaving 30% of pixels as grayscale), and at 20% from each extreme for low contrast (leaving 60% grayscale). The averaged root mean squared (RMS) values, which correspond to the standard deviation of the pixel intensities (Peli, 1990), were computed for each contrast level. RMS scores were 122.2 ($SD=4.7$), 92.35 ($SD=8.5$), and 65.7 ($SD=10.5$) for high, mid and low contrast respectively. According to (50), the *FD* is not affected by changing the contrast of the image. We validated that the *FD* did not differ between contrast levels by applying the differential box-counting method (Kolekar et al., 2000), which allows us to compute *FD* on grayscale images. In the end, we have a set of 1080 images (360 images X 3 contrast levels) that was divided into three new sets of 360 images with distinct patterns for each contrast level. The images from the three sets were randomly assigned to the 50 participants. This procedure allows us to have the same images with different contrast levels in our full dataset, without the drawback of presenting images with the same structures and varying contrast levels to the same participant.

Pareidolia measures

Pareidolia was assessed based on three indicators: reaction time (*RT*), pareidolia occurrence (*Par*) and number of objects perceived (*N_obj*). *RT* corresponds to the time between stimulus onset and first pareidolic perception. Pareidolia (*Par*) is a value between 0 and 1 representing the proportion of trials in which one or more pareidolic perceptions occurred. *Par* thus aims to capture participants' flexibility, defined as the capacity to experience pareidolia in a wide range of stimuli. Number of objects (*N_obj*) represents the average number of pareidolic percepts on trials during which pareidolia occurred, and aims to capture the fluency aspect of

pareidolia, i.e. the capacity to fluently modulate perceptions within the same stimulus. Finally, a measure of spontaneous pareidolia (*Spont_par*) was derived by computing the proportion of trials where pareidolia was reported within the first two seconds, compared to the total number of trials where pareidolia was reported. Several threshold values (1.5/2/2.5sec) were tested to ensure that our results are consistent (see **Fig S2.3** for more details). Spontaneous pareidolia serves as a complementary measure of reaction time designed to target the trials that are likely to reflect the spontaneous emergence of pareidolic percepts.

Statistical analysis

Initial analyses.

To confirm that stimulus properties are related to pareidolia, we examined the linear and quadratic relation between *FD* and pareidolia with Pearson correlation, and performed a repeated-measure ANOVA to investigate the effect of contrast on pareidolia. We also ran image-based analyses to check whether there was some evidence for consistency across participants in their responses to identical stimuli. First, we computed the mean value of pareidolia occurrence and number of percepts reported for each single image. We then computed new means for the same variable but this time after randomly shuffling the provided responses across all stimuli (as a realization of a mean of random responses for each stimulus). Most importantly, we tested the differences between the distribution of the original pareidolia response data and 1000 randomized sets of responses using two-sample Kolmogorov-Smirnov tests. We also conducted a Shapiro-Wilk test of normality on each of our variables presented in **Figure 2.3**. (see **Fig S2.4**.)

Generalized Linear Mixed Effect Model.

Generalized Linear Mixed Effects Models (GLMM) are regression models that allow using non-normally distributed dependent variables and including random effects to model variables from different nested levels (Bates et al., 2015a). By incorporating the variability inherent to nested

variables, GLMM is a family of statistical models that allows the modelling of cross-level interactions. In the present case, the first level corresponds to the trial level, comprising pareidolia variables, *FD* and contrast, while the second level corresponds to the participant level, comprising questionnaire variables (creative phenomenology, *Crea_pheno*). Hence, the use of GLMM enables us to include all the inherent variance in the data, and investigate first- and second-level variabilities simultaneously within a single model.

Two predictors (*Crea_pheno*, *FD*) were centered around the grand mean, while *contrast* was transformed into a binary variable based on preliminary analyses. To do so, medium and low contrast images were treated together as opposed to high-contrast images. Random slopes were also included for *FD* terms following guideline that suggests including random slope for any within-unit factor (Barr, 2013). When the predicted variable was *Par*, a binomial distribution with a logit link function was specified to best fit the binary outcome, while when the predicted variable was *N_obj*, a zero-truncated negative binomial distribution was specified. For our third dependent variable, RT, a logarithmic link function was specified. To achieve a good fit to the data with a GLMM, successive models were constructed and compared with each other while the level of complexity was increased at each iteration. To quantify the superiority of one model over another, ANOVAs comparing the Akaike Information Criterion (AIC) of two models were computed (Royle, 2013).

Principal analyses.

We first tested whether creativity measures were correlated with pareidolia (averaged across all trials for each participant) using Spearman correlation. We then ran a Generalized Linear Mixed-effect Model (GLMM) that models the moderation effects of contrast and *FD* (both linear and quadratic terms) on creativity. To explore further the moderator effect of *FD* on the relation between creativity and pareidolia, we (1) ran regression analyses to predict pareidolia

from creativity scores for each *FD* (Bonferroni corrected), (2) examined the quadratic relation between *FD* and pareidolia for high- and low-creatives and (3) ran the GLMM replacing *Crea_pheno* by the measure of divergent thinking (see Supplementary Materials).

Data and code availability

Original code has been deposited at Figshare repository and is publicly available as of the date of publication. (<https://doi.org/10.6084/m9.figshare.19469957.v2>)

Neural signatures of divergent perception are modulated by creativity and stimulus complexity

Abstract

Creativity is a multifaceted skill that has traditionally been explored through divergent thinking methodologies, entailing the generation of multiple solutions to a given problem. This study explores the neural basis of divergent perception, the perceptual analog of divergent thinking, which consists in identifying various perceptual interpretations of a given sensory stimulus. By doing so, we aim to examine the influence of creativity and the complexity of visual stimuli on brain activity related to divergent perceptual processes. To identify neural markers of pattern recognition in ambiguous visuals, we recorded participants' brain activity with magnetoencephalography (MEG) as they identified objects in fractal images, inducing unconstrained pareidolia. Notably, after removing the aperiodic component of the neural signal to accurately estimate oscillatory processes, changes in theta, alpha and gamma brain oscillations were observed. This finding challenges existing views on the neural mechanisms in perceptual binding and suggests a broader spectrum of oscillations involved in sensory integration. The study shows an inverse correlation between the complexity of fractal stimuli and brain signal complexity in occipital regions, which transitions to a positive correlation with increasing pareidolic fluency. Fractal dimensions significantly influence brain responses in pareidolic experiences, suggesting dynamic adaptation to external stimuli and a fractality matching in altered perceptual states. Moreover, we found that neural responses associated with pareidolia, as well as spontaneous brain activity following the pareidolia task, vary as a function of creativity levels. Conclusively, this research sheds light on the neural mechanisms of unconstrained pareidolia, underscoring the influence of creativity and stimulus complexity on perception of ambiguous stimuli. It advances our understanding of sensory integration and visual perception, emphasizing the interaction between internal cognitive states, external sensory information, and individual creativity levels.

Introduction

Humans, as meaning-making organisms, constantly seek to integrate complex stimuli into structured object representations. This quest to understand perceptual coherence has been a central theme in cognitive neuroscience, particularly in the study of perceptual binding. Historically, research in this domain, inspired by Gestalt theory, predominantly leveraged the use of ambiguous or multistable stimuli to probe neural markers of perceptual switching. Such studies have underscored the role of brain oscillations, particularly gamma activity (Ding et al., 2017; Ehm et al., 2011; Rodriguez et al., 1999; Tallon-Baudry & Bertrand, 1999) and other frequency bands (Klemm et al., 2000), in perceptual emergence. The advent of transcranial alternating current stimulation (tACS) techniques further refined our understanding by effectively modulating oscillatory activity and behavioral performance in spatial and spatio-temporal binding tasks (Ghiani et al., 2021). However, these strides have been confined to highly controlled experimental settings—characterized by rigidly structured tasks, predetermined stimuli, and limited perceptual choices—resulting in an underrepresentation of perception in real-world scenarios. Our understanding of how the brain processes spontaneous and unstructured perceptual experiences remains elusive, leaving a significant gap in our knowledge of perceptual dynamics in naturalistic contexts.

Recent research has explored the relation between perception of ambiguous stimuli and creative cognition, shedding light on the variations in perceptual processing across individuals. Studies have demonstrated that exposure to ambiguous images can improve performance in creative writing and divergent thinking tasks (X. Wu et al., 2019). Additionally, increased perceptual switching rates when viewing multistable images has been linked to creative capabilities (Bergum & Bergum, 1979; Blake & Palmisano, 2021; Rodríguez-Martínez, 2023) underscoring a deep connection between the interpretation of ambiguous visual information and creative thought processes (Beghetto, 2019; Beghetto & Jaeger, 2022; Gabora, 2016). However,

research has yet to thoroughly investigate the neural underpinnings that characterize how individuals with differing levels of creativity perceive ambiguous stimuli.

Addressing this gap, the current study explores the neural underpinnings of unconstrained pareidolia, a phenomenon where meaningful percepts spontaneously emerge from ambiguous stimuli, such as seeing faces in the moon or animals in cloud formations. This naturalistic approach deviates from traditional paradigms by not limiting perceptual awareness to two perceptual options (bistability), thereby providing a unique opportunity to examine the interplay between top-down (feedback) and bottom-up (feed-forward) processes in perception. The importance of this investigation lies in its potential to offer insights into how the brain integrates internal cognitive states with external sensory information, and the role of creativity in interpreting ambiguous visual stimuli.

Methodologically, our study introduces an innovative approach by employing fractal images to stimulate pareidolia while recording electromagnetic brain signals of the participants. This choice is grounded in evidence suggesting that fractal images, characterized by their complexity, are particularly conducive to eliciting pareidolic experiences (Bellemare-Pepin et al., 2022; A. Bies, Boydston, et al., 2016; Rogowitz & Voss, 1990a; Taylor et al., 2017b). Furthermore, recent studies have indicated a link between individual creativity levels and the frequency of pareidolic percepts (Bellemare-Pepin et al., 2022; Diana et al., 2021), suggesting that creative individuals experience pareidolia more easily and across a wider range of visual complexity.

The neural markers of pareidolia remain largely elusive. Functional magnetic resonance imaging (fMRI) studies indicate that face-pareidolia involves cooperation between top-down and bottom-up brain regions, particularly the fusiform face area and frontal and occipitotemporal areas (Akdeniz et al., 2018; Liu et al., 2014b; Wardle et al., 2020). Recent electrophysiological studies on face pareidolia, using pre-stimulus brain activity (Barik et al., 2019) and Event-Related Potential paradigms (Akdeniz, 2020), indicate its emergence in early visual processing and

underscore the significance of expectation. Growing evidence suggests that oscillatory brain activity, crucial for binding sensory information (Ghiani et al., 2021), may not fully account for the emergence of perception. Accordingly, recent work underscores the importance of brain fractality and complexity measures in accounting for both perceptual emergence (Grosu et al., 2023) and altered perceptual states (Carhart-Harris, 2018b; Van Eyghen, 2023). Brain fractality, reflecting scale-freeness, effectively distinguishes between internally and externally generated percepts (Ibáñez-Molina & Iglesias-Parro, 2014), as well as between visual perception and imagination (Lutzenberger et al., 1992). Additionally, this concept has been proposed as a framework for understanding how the environment constraints scale-free brain dynamics, integrating brain, body, and environmental interactions (Grosu et al., 2023). In the naturalistic context of unconstrained pareidolia, in which both perception (external) and imagination (internal) are involved simultaneously, these studies suggest that brain fractality and complexity measures are well suited to characterize perceptual emergence.

This study focuses on two primary objectives: first, to investigate the neural dynamics and characterization of unconstrained pareidolia by using fractal stimuli in naturalistic settings; and secondly, to examine the interplay between creativity, divergent perception, and stimulus properties, particularly focusing on how visual complexity processing is modulated by creativity levels. These goals collectively provide a detailed understanding of unconstrained pareidolia, its connection to creativity, and the impact of stimulus characteristics. To address the first objective, we will identify the neural processes associated with the experience of unconstrained pareidolia by comparing brain activity during pareidolic and non-pareidolic states, with the hypothesis that pareidolia will manifest through distinct brain patterns indicative of top-down processes. We will further characterize spontaneous pareidolia by comparing brain dynamics for early and late pareidolia. Spontaneous pareidolia is anticipated to correlate with a decrease in inhibition and an augmentation in sensory processing, likely denoted by decrease in alpha power and increased

gamma activity. The second objective will be explored by investigating the relationship between the fractality of both visual stimuli and brain activity, as well as how this relationship might be influenced by creativity levels and pareidolic experiences. We anticipate a correlation between the fractal dimensions of brain signals and visual stimuli in the occipital areas, modulated by the presence of pareidolia. We will further characterize the changes in spontaneous brain activity before and after engaging in a pareidolia task, looking at how creativity and pareidolia during the task influence these changes. We hypothesize that brain activity post-task will significantly differ from pre-task activity, and that this difference will be influenced by levels of creativity, bringing insights into how creative individuals differ in their cognitive processes while engaging in a pareidolia task. Finally, we will explore the impact of suggestion on pareidolic perception, exploring how belief or expectation can lead to perceptual placebo. By investigating the neural correlates of pareidolia through fractal stimuli, this study aims to reveal insights into perceptual processing of ambiguous stimuli, with direct implications for enhancing our understanding of how sensory integration and visual perception relate with creative cognition.

Methods

Participants

Twelve neurotypical individuals (3 females) between the ages of 19 and 37 ($M = 28.5$, $SD = 4.3$) participated in this study. The experiment was approved by the Neuroimaging Aging Research Ethics Committee (CER-VN-19-20-08), and all participants provided written informed consent prior to their involvement.

Stimuli

To examine the neural correlates of pareidolic perception, we generated ambiguous visual stimuli that consisted of images of varying fractal dimension (FD). FD quantifies the complexity of

patterns across varying scales of observation (Spehar et al., 2003). Various algorithms exist for computing FD (Lopes & Betrouni, 2009). Images with lower FD are less detailed, while those with higher FD are more intricate and complex (Cutting & Garvin, 1987b; Gilden et al., 1993; Pentland, 1984). Fractals are categorized as either exact or statistical. Exact fractals have a repetitive geometric pattern at different magnifications, whereas statistical fractals show randomness, leading to similarities but not exact repetition at various scales. More specifically we created statistical fractal images using $1/f$ noise (Lennon, 2000b) and the inverse discrete Fourier Transform. This method allowed precise control over the FD of each image. A range of images with FD values from 1.05 to 1.95 were created, spread across 13 evenly spaced FD levels.

A total of 416 images, each 1024 by 1024 pixels, were produced. These images were modified to create two levels of contrast. For high contrast, images were thresholded at the mean luminance level, setting half the pixels to black and the other half to white (Spehar et al., 2016). The low contrast level was achieved by thresholding at 25% from each end of the luminance spectrum, maintaining 50% of the pixels in grayscale. The root mean squared (RMS) values, reflecting the standard deviation of pixel intensities (Peli, 1990), were calculated on each image rescaled between 0 and 1, for the two contrast levels, resulting in RMS values of 0.7 (SD = 0.07) for high contrast and 0.6 (SD = 0.07) for low contrast. Rescaling images to a 0-1 intensity range before RMS computation standardizes the contrast metric across varying noise levels, allowing for a more accurate comparison of inherent contrast variability within the fractal patterns, independent of their absolute intensity range. Previous research indicates that FD remains consistent across different contrast levels (Spehar et al., 2016). This was confirmed in our study using the differential box-counting method (Kolekar et al., 2000), a technique suitable for grayscale images, verifying that FD did not vary with contrast changes. Ultimately, the set of 416 images (13 FD levels \times 2 contrast levels \times 16 images per category) was divided into 8 blocks of 52 images each. The method employed for generating fractal images is identical to that utilized

in our previous study, which elicited variable levels of pareidolia among participants (Bellemare-Pepin et al., 2022).

Experimental Design

The first phase of the experiment involved a 3-minute resting-state recording with eyes open. The participants were then introduced to the main task, in which they were asked to fixate the center of the screen and to respond using one 5-button controller for each hand, with a button placed under each finger. The participants' primary task was to identify as many objects as possible within the 8-second presentation of each stimulus, displayed in a pseudo-random sequence. They were instructed to press the button with the index of the corresponding hand upon perceiving the first object in the stimulus. To minimize motor lateralization effects on the MEG signal, the hand used for responding alternated with each block. The displayed images were sized to cover approximately 10 degrees of visual angle. Each stimulus was preceded by a fixation cross for a duration of 1.5 seconds. Following each stimulus, participants reported the total count of perceived objects on a scale ranging from 0 to 5-and-above (see **Fig. 3.1A**). We refer throughout the manuscript to the presence or absence of pareidolia within a trial as *pareidolia occurrences* and to the number of percepts in each trial when pareidolia was reported as *number of percepts*. This experimental design has been validated in a previous behavioral study (Bellemare-Pepin et al., 2022)

To familiarize participants with the task, a practice block of 10 trials was conducted before the main experiment. To encourage participants to respond truthfully about pareidolia occurrences, they were informed that the image where they reported the highest number of objects will be reviewed with them at the end of the experiment. Throughout the experimental procedure, the term "creativity" was deliberately avoided to prevent participants from feeling pressured to perform well on a 'creativity test'. Instead, participants were informed that the study focused on perception, likening the task to a game of finding shapes in clouds, emphasizing that

there were no right or wrong answers. The experimenter remained present during the practice block to address any queries. The MEG part of the experiment lasted a little over one hour, segmented into six 10-minute blocks and followed by a second 3-minute eyes open resting state. Participants were offered short breaks every two blocks, as needed.

Following the initial six blocks, participants were given the choice to engage in two more sham blocks (see **Fig. 3.1B**). At this juncture, they were informed that during the first six blocks, an artificial intelligence algorithm had been learning which fractal images most effectively enhanced their pareidolia. In the subsequent two blocks, participants were briefed that the algorithm would generate individualized stimuli that are designed to maximize or minimize their pareidolic experience in each of the two blocks. The order of these blocks was alternated between participants. This segment of the study aimed to investigate the effects of suggestion on divergent perception and to examine how individual creativity levels modulated these effects. Out of the 12 participants, 8 consented to complete the two sham blocks.

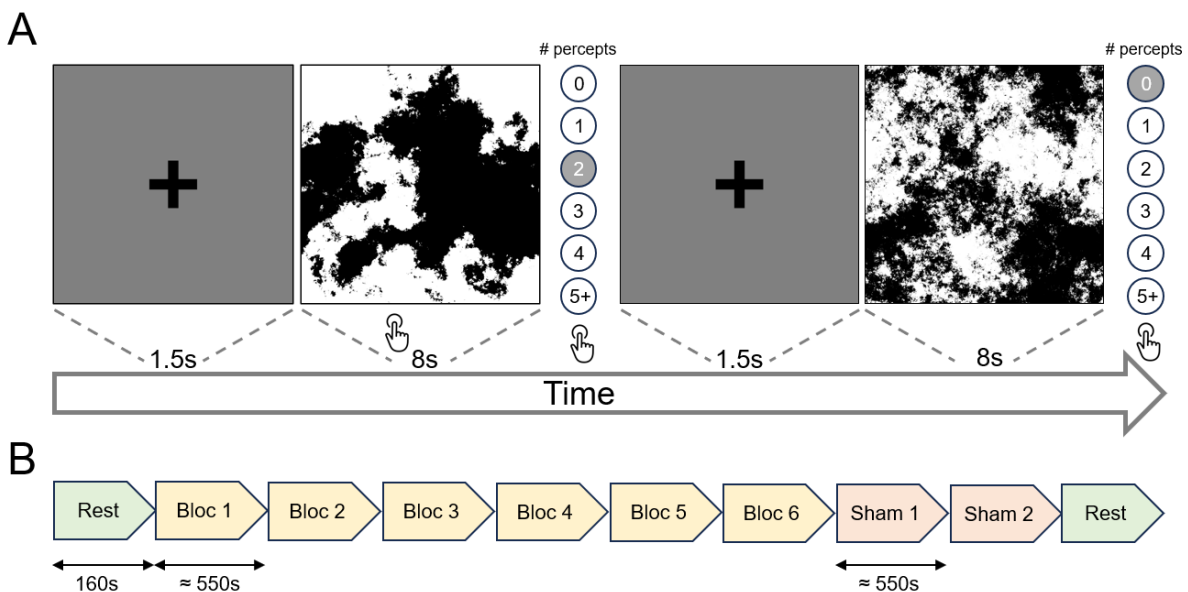


Figure 3.1. Experimental design of the pareidolia task. (A) Example of a trial sequence. Each trial starts with a fixation cross, followed by an image presentation during which the participant has to click when a first percept is detected. After each image, the number of percepts is reported. **(B)** Experiment structure. Sessions include 10 runs with an opening eyes-open rest, 6 task blocks, 2 optional placebo blocks, and a closing resting state.

Creativity assessment

To measure creativity, we relied on the Divergent Association Task (Olson et al., 2021), a measure of semantic creativity which requires the participant to find 10 words that are the most semantically distant from one another. The creativity score derived from this task is calculated by determining the average semantic distance between the selected words. Crucially, performance on the DAT is closely linked with results from two established creativity tests: the Alternative Uses Task and the Bridge-the-Associative-Gap Task (Olson et al., 2021). The DAT test was administered following the MEG test to prevent priming the participants and to mitigate any doubts regarding the significance of creativity in the experiment.

MEG analysis

Acquisition

Brain imaging data were acquired using a 275-channel CTF MEG system. Eye movements and heart rate were tracked using vertical and horizontal EOG and ECG channels, respectively (Messaritaki et al., 2017). The head shapes were scanned using a Polhemus Fastrak digitization system. Head movement was tracked at the start and end of each session using localization coils placed at the left and right pre-auricular points and the nasion, ensuring that head displacement did not exceed 10mm throughout the session. Once set up, participants were instructed to remain still throughout the recording. The MEG signals were captured at a high-resolution sampling frequency of 1200Hz, with a hardware lowpass filter at 300 Hz. Visual stimuli were presented as images subtending 8-° of visual angle.

Preprocessing and Epoching

The preprocessing and epoching procedures were conducted with MNE-python (Gramfort et al., 2014). MEG data were filtered with a high-pass of 0.5 Hz and a low-pass of 200 Hz, with

additional 60 Hz notch filtering to suppress electrical line noise. Independent Component Analysis (ICA) with 20 components was employed for artifact correction, identifying and excluding components associated with eye blinks and cardiac signals. This process was systematized across all participants to ensure uniform data treatment. After artifact rejection, the integrity of the data was confirmed through visual inspection using generated report figures.

For the epoching, two distinct strategies were implemented. The first epoching strategy was employed to precisely target the onset of the pareidolic percept. This involved analyzing the data from -1.5 to -0.5 seconds relative to the button press, with a baseline period established between -2.5 and -1.5 seconds prior to the button press. To ensure that the analysis was focused on the perceptual aspects of the task and not confounded by motor planning components, the 500 milliseconds immediately preceding the button press were intentionally excluded from this analysis. Previous studies on ambiguous stimuli suggest that perceptual reversal occurs at least 340 milliseconds before an observer can consciously report the change (Kornmeier & Bach, 2012). For trials with no reported pareidolia, epochs were selected around the mean reaction time of the participant. The second epoching strategy involved analyzing the entire 8-second duration of stimulus presentation, with a baseline period defined during the fixation cross, from -1 second to the onset of the stimulus. This epoching was primarily designed to explore the relationship between stimulus FD and brain FD, and to investigate the modulatory effects of pareidolia and creativity levels. This two-pronged epoching approach allowed for a comprehensive investigation of both the broader neural correlates associated with stimulus characteristics and the more specific neural events leading up to the recognition of a pareidolic percept. For the resting state blocs, the 3 minutes were decomposed into 3 seconds epochs, for a total of 60 epochs per bloc.

Feature extraction

We set out to probe the role of various types of MEG features, including its spectral properties (both periodic and aperiodic components of the power spectrum) and complexity

related metrics (Lempel-Ziv complexity, the Hurst exponent and long-range temporal correlations) To dissociate between physiological oscillations and the aperiodic component (1/f slope exponent) of the spectrum, we used the *Spectral parameterization (specparam)* python toolbox (Donoghue et al., 2020). The 1/f exponent within this framework quantifies the long-range dependencies within the signal, where a value of 1 (pink noise) indicates fractal patterns with self-similar properties across time scales. A value of 0 (white noise) denotes randomness with no correlation between sequential points, and a value of 2 (brown noise) suggests a random walk with strong time-dependent correlations, emphasizing lower frequencies.

To estimate the 1/f exponent of the signal, we first estimated the Power Spectral Density (PSD) across specific frequency bands (theta [4-8 Hz], alpha [8-12 Hz], low_beta [12-20 Hz], high_beta [20-30 Hz], gamma1 [30-45 Hz], gamma2 [45-60 Hz], and gamma3 [60-90Hz]) using the Welch Method with parameters $nfft=1200$ and $nperseg=nfft/4$. We probed all frequencies between 4 and 90Hz, aligning with recent recommendations suggesting that lower frequency components (i.e. delta band) could introduce complexities in fitting and estimating the aperiodic component, as evidenced by the potential overlap of oscillatory peaks with fitting range borders and the consequent distortion in estimating the 1/f exponent (Gerster et al., 2022). The length of 1s of our epochs allowed for a minimum of 4 cycles of the lower frequency in the PSD computation. To mitigate the noisiness of the spectrum computed on such short time-windows, we averaged the spectrum for each run and participant, across the two conditions of interest. This averaged spectrum was then used to estimate the aperiodic component using FOOOF. Finally, we removed the run-level aperiodic component from each epoch.

For assessing signal complexity, Lempel-Ziv complexity (LZC), a technique valuable for quantifying signal diversity (Lempel & Ziv, 1976), was calculated on the binarized version of the signal using the Antropy Python package. In addition, scale-freeness of the neural signals was evaluated using five distinct metrics. The Hurst exponent and Detrended Fluctuation Analysis

(DFA), both associated with long-range temporal correlations, were applied to normalized signals to evaluate persistent patterns and scaling behavior over time. As supplementary analyses, the fractal dimension of brain signal was further assessed using Higuchi's, Petrosian's, and Sevcik's algorithms. Refer to supplementary material for more details on the use of these metrics. These metrics were chosen for their complementarity, and were used in previous studies exploring the complexity of M/EEG brain data (Farnes et al., 2020; S. Geng et al., 2011; La Rocca et al., 2018; Van Eyghen, 2023). Together, these metrics offer a comprehensive view of the neural signal's complexity and self-similarity, crucial for understanding the neural correlates of perceptual emergence and unconstrained pareidolia.

Generalized linear mixed-effect models (GLMMs)

To leverage maximum information from our data and effectively handle nested variables at both the trial and participant levels, we utilized Generalized Linear Mixed Effects Models (GLMM). This approach is a type of regression model designed for dealing with dependent variables that don't necessarily follow a normal distribution and for incorporating random effects to handle data from multiple nested levels (Bates et al., 2015b). In our study, the first level pertains to the trial level, which includes variables like pareidolia, FD, features of brain activity. The second level relates to the participant level and includes the creativity score. The use of GLMM allows us to account for the inherent variance in our data and to explore variabilities at both the trial and participant levels within a single model. We built a GLMM for each electrode and systematically included a random intercept to account for individual differences among participants. Informed by model comparisons using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), our approach prioritized model parsimony and optimal data fit.

In our examination of the neural correlates associated with the onset of a specific pareidolic perception, we utilized a Generalized Linear Mixed Model (GLMM) with a binary outcome (see **Table 3.1 - Formula 1**). This model was designed to predict the occurrence of

pareidolia based on power in spectral bands, LZC, FD, and level of creativity. All predictors were centered around the grand mean. Crucially, the model accounted for the interaction between brain characteristics and creativity. Additionally, the model integrated a random slope for FD and its quadratic term, aligning with findings showing an inverted U-shaped relationship between stimulus FD and pareidolia emergence (Bellemare-Pepin et al., 2022). Our analysis further extended to the prediction of brain fractal dimension (bFD), employing a GLMM outlined in **Table 3.1 - Formula 2**. The model incorporated FD, DAT levels, and the number of pareidolic percepts (n_{obj}) as predictors as well as all their interaction terms. The models predicting Hurst and DFA also incorporated the stimulus contrast as a predictor. Another GLMM was constructed to predict resting state condition (pre vs post), incorporating brain features as predictors, along with their respective interaction terms with individual DAT score and average pareidolia occurrence during the task (refer to **Table 3.1 - Formula 3**). Similarly, a GLMM was built to assess the influence of sham condition on pareidolia, incorporating both the main effects and the interaction between sham condition number and DAT score, while accounting for the variability attributed to individual participants and the random effect of FD. The mathematical representation of the model (**Table 3.1 - Formula 4**) is as follows:

| Description | Epochs | Formula |
|--|--------------------------------------|--|
| (1) Model predicting pareidolia occurrences and interaction with creativity. | Pre button press (-1.5, -0.5) | $parei \sim FD + FD^2 + contrast + (\theta + \alpha + \beta_{low,high} + \gamma_{1,2,3} + LZ) \times DAT + (1 + FD + FD^2 subj)$ |
| (2) Model predicting brain fractal dimension (bFD) | Full epoch (0, 8) | $bFD \sim FD \times DAT \times n_{obj} + (1 subj)$ |
| (3) Model predicting resting state from brain features, creativity, and pareidolia | Resting State 3 seconds epoch (0, 3) | $RS \sim (\theta + \alpha + \beta_{low,high} + \gamma_{1,2,3} + LZ) \times DAT \times parei_{avg} + (1 subj)$ |
| (4) Model assessing the influence of suggestion on pareidolia | NA | $parei \sim sham_{cond} \times DAT + (FD subj)$ |

Table 3.1. Description of the generalized linear mixed-effect models and their formulas.

Classification using supervised machine learning

In order to classify resting state conditions (pre- vs post-task), we employed a random forest classifier, using all PSD features corrected after removal of the aperiodic component, as well as LZC (Pedregosa et al., 2011). To ensure robust cross-validation, a stratified group k-fold approach was adopted, with the number of folds equal to the total number of subjects ($k=12$). Hyperparameter tuning was conducted through a random search methodology (see **Table 3.2**). The primary metric for evaluating model performance was balanced accuracy and significance level was determined using permutation test ($n = 1000$). Multiple comparisons were accounted for using the maximum statistics method (Neuhäuser & Hothorn, 2006).

| Parameter | Values |
|--|--------------------|
| Number of Estimators (<i>n_estimators</i>) | 50, 100, 200, 300 |
| Maximum Depth (<i>max_depth</i>) | 2, 6, 10, 20, None |
| Criterion (<i>criterion</i>) | gini, entropy |
| Minimum Samples Split (<i>min_samples_split</i>) | 2, 5, 10 |
| Minimum Samples Leaf (<i>min_samples_leaf</i>) | 1, 2, 4 |

Table 3.2. Hyperparameter distributions for random forest classifier

Results

Effect of fractal dimension on pareidolia

To evaluate the relation between stimulus FD and pareidolia, we ran quadratic regression and found significant inverted U-shape for pareidolia occurrences across high ($F(2, 10) = 6.60, p = 0.015, R^2 = 0.57$) and low ($F(2, 10) = 26.79, p < 0.001, R^2 = 0.84$) contrasts as well as for the number of percepts ($F(2, 10) = 97.80, p < 0.001, R^2 = 0.95$) during pareidolia trials for high ($F(2, 10) = 56.00, p < 0.001, R^2 = 0.92$) and low ($F(2, 10) = 7.88, p = 0.009, R^2 = 0.61$) contrasts (see **Fig. 3.2**). These results replicate ones previously found in the literature (Bellemare-Pepin et al., 2022).

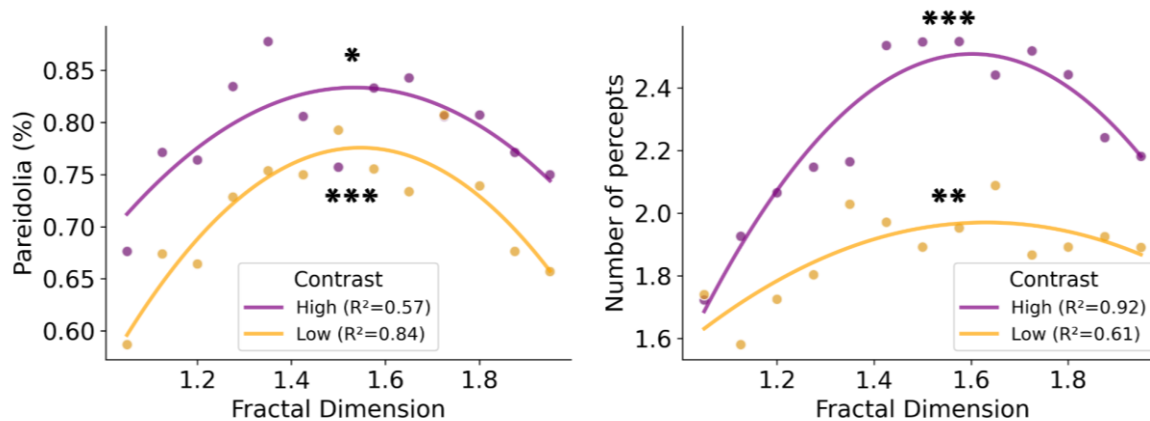


Figure 3.2. Relation between stimulus fractal dimension and pareidolia. The left panel illustrates the relation between stimulus FD and mean pareidolia occurrences across subjects (a pareidolia occurrence of 50% implies half of the trials were associated with reported pareidolia). The right panel illustrates the relation between stimulus FD and the number of percepts on trials with at least one reported percept. ***: $p < .001$.

Predicting pareidolia with oscillations and complexity metrics

In examining the neural dynamics linked to the emergence of the first pareidolic percept, we employed oscillatory components, isolated by the exclusion of the aperiodic component, alongside LZC as predictive factors. This approach was applied within one-second epochs preceding the behavioral response, as depicted in **Figure 3.3A**. The use of oscillatory components provided insight into the rhythmic neural activity, while LZC offered a measure of the signal's diversity. The analysis of the aperiodic component across subjects and sensors, in both pareidolia and non-pareidolia trials, indicated a trend of reduced exponent values in the left hemisphere during pareidolia trials, as depicted in the topological distribution in **Figure 3.3B**. Additionally, the overall scalp distribution of exponents was found to be significantly lower in pareidolic trials ($t = 13.84$, $p = 2.9e-33$, $df = 269$).

The fixed effects analysis of brain features (see **Fig. 3.3A**) revealed a notable increase in theta (*effect sizes: 0.27 to 0.47*, $p_{range}: 0.007$ to $2.1e-06$) and LZ (*effect sizes: 0.26 to 0.43*, $p_{range}: 0.002$ to $2.3e-07$), as well as a decrease in alpha band (*effect sizes: -0.35 to -0.64*, $p_{range}: 0.007$ to $1.2e-06$) within the frontal regions during pareidolia. To evaluate whether the effect of LZC was

not attributable to ocular movements, we tested the same model using the LZC of the electrooculogram (EOG) as a predictor. The results indicated no significant effect of EOG LZ complexity on pareidolia occurrences (*effect size*: -0.57, $p = 0.68$, $df = 3630$), suggesting that the variations in brain LZC are not due to ocular artifacts. Additionally, a reduction in gamma₁ activity was observed in the right central region (*effect sizes*: -0.27 to -0.29, p_{range} : 0.001 to 3.1e-05). Significant interactions were found between individual creativity levels and gamma1 band activity in the right central area (*effect sizes*: 0.22 to 0.25, p_{range} : 1.8e-04 to 2.3e-03). This interaction implies that in highly creative individuals, an increase in gamma power (30-45Hz) is associated with an increase in the likelihood of experiencing pareidolia, while for less creative individuals, the opposite trend is observed, as shown in **Figure 3.3C**.

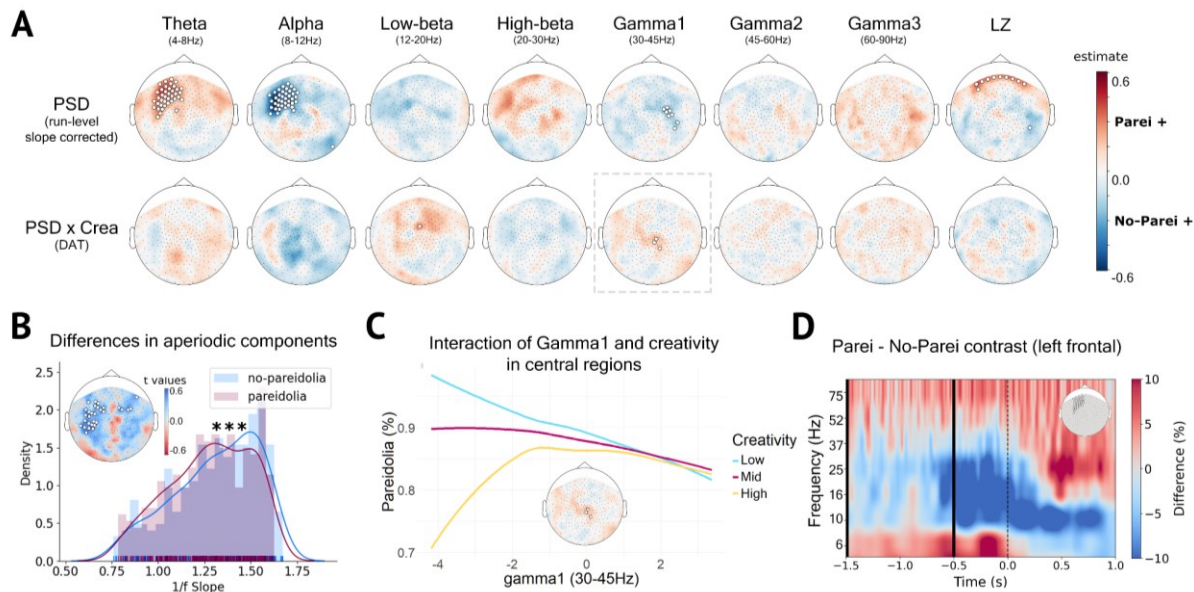


Figure 3.3. Predicting pareidolia based on spectral power, complexity and interactions with creativity. (A) Topographic maps illustrating the predictive power of EEG spectral power and LZ complexity on the propensity for pareidolia, corrected for the aperiodic component. First row represents the fixed effect of each predictor, while the second row represents the interaction effect of each predictor with creativity score (DAT). White dots indicate regions where predictions are statistically significant ($p < .05$) following False Discovery Rate (FDR) correction. $N_{obs} = 3344$. (B) Distribution of the $1/f$ slope exponent across sensors (***: $p < .001$). Topological distribution representing significant sensors ($p < .05$), uncorrected for multiple comparisons. (C) Interaction between each brain feature and creativity scores, revealing regions where creativity significantly modifies the predictive power. (D) Time-frequency map of the amplitude envelopes of each band in the frontal left region, using Hilbert transform. The epochs used for the analyses in (A) are between -1.5s and -0.5s.

Predicting early vs. late pareidolia

To explore the difference in brain dynamics between early and late pareidolia, we ran a GLM using PSD estimates and LZC as predictors (see **Fig. 3.4A**), on the same one-second epochs as for the previous analysis. The analysis of the aperiodic component across subjects and sensors, in both early and late pareidolia trials, indicated a trend of increased exponent values in the central region during early trials, as depicted in the topological distribution in **Figure 3.4B**. Additionally, the overall scalp distribution of exponents was found to be significantly higher in early pareidolia trials ($t = 7.43$, $p = 1.4e-12$, $df = 269$). The fixed effects of our predictors revealed a significant increase of theta activity in central, parietal and occipital regions (*effect sizes: -0.34 to -0.52*, $p_{range}: 0.0001$ to $2.7e-09$), as well as a widespread increase of low- (*effect sizes: -0.37 to -0.73*, $p_{range}: 0.0002$ to $7.9e-09$) and high-beta activity (*effect sizes: -0.41 to -0.47*, $p_{range}: 2.2e-06$ to $2.1e-06$) during early pareidolia trials. We also found that early pareidolia is associated with significant increases in alpha synchronization in central regions (*effect sizes: 0.60 to 0.62*, $p_{range}: 3.9e-06$ to $2.9e-06$) and desynchronization in temporal regions (*effect sizes: -0.52 to -0.60*, $p_{range}: 0.0002$ to $9.9e-06$). We further uncovered significant increases in gamma3 power in occipital regions (*effect sizes: -0.26 to -0.37*, $p_{range}: 2.1e-05$ to $1.3e-08$), as well as widespread decreases in posterior LZC (*effect sizes: 0.32 to 0.42*, $p_{range}: 4.0e-05$ to $1.9e-06$).

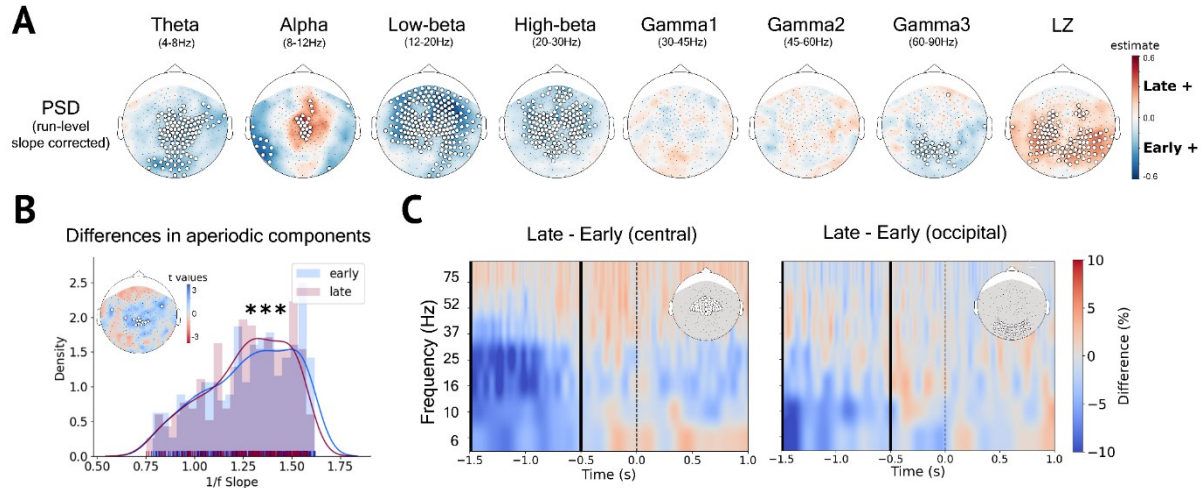


Figure 3.4. Predicting spontaneous pareidolia based on spectral power and complexity. (A) Topographic maps illustrating the predictive power of EEG spectral power and LZC on early (spontaneous) vs. late pareidolia, corrected for the aperiodic component. White dots indicate regions where predictions are statistically significant ($p < .05$) following False Discovery Rate (FDR) correction. $N_{obs} = 2301$. (B) Distribution of the $1/f$ slope exponent across all sensors (***: $p < .01$), topological distribution representing significant sensors ($p < .05$), uncorrected for multiple comparisons. (C) Time-frequency maps of the amplitude envelopes of each band in the frontal (left plot) and occipital (right plot), using Hilbert transform. The epochs used for the analyses in (A) are between -1.5s and -0.5s.

Modeling the interaction of image fractality, pareidolia and creativity on brain fractality

Separate models were constructed to predict each of the selected brain fractal dimension metrics, incorporating creativity, stimulus FD, and the number of percepts as predictors. For both bFD estimates, the Hurst Exponent and DFA, higher values indicate lower complexity and greater self-similarity, assessing the long-range temporal correlation properties of the signal. Fixed effects showed that higher numbers of pareidolic percepts are associated with significant increases of both Hurst Exponent (*effect sizes: 0.006 to 0.02, p_{range} : 0.01 to 2.9e-08*) and DFA (*effect sizes: 0.01 to 0.02, p_{range} : 0.002 to 8.3e-05*) in occipital regions (see **Fig. 3.5A-C**). This effect spreads to the left parietal region for Hurst Exponent. Moreover, a positive correlation was observed between stimulus FD and DFA in the occipital regions (*effect sizes: 0.01 to 0.03, p_{range} : 0.005 to 3.2e-06*), while Hurst exponents were higher for high-contrast images in the same regions (*effect sizes: -0.003 to -0.005, p_{range} : 0.01 to 7.7e-06*). Significant interaction effects were also detected between the number of pareidolic percepts and stimulus FD for both Hurst Exponent (*effect sizes: -0.004*

to -0.01 , p_{range} : 0.006 to $2.5e-07$) and DFA (effect sizes: -0.008 to -0.01 , p_{range} : 0.002 to $2.3e-04$) in the occipital areas (see **Fig. 3.5B-D**). This interaction indicates that, at higher pareidolic percept counts, there is a negative correlation with stimulus FD for both Hurst Exponent and DFA, while at lower percept counts, the correlation turns positive for DFA and becomes non-significant for Hurst Exponent. Complementary analyses using three alternative fractal dimension measures revealed significant predictive power of stimulus FD in occipital regions. Complementary analyses employing three alternative fractal dimension measures revealed that the fractal dimension of the stimulus significantly predicted activity in the occipital regions (refer to **Fig. S3.1**)

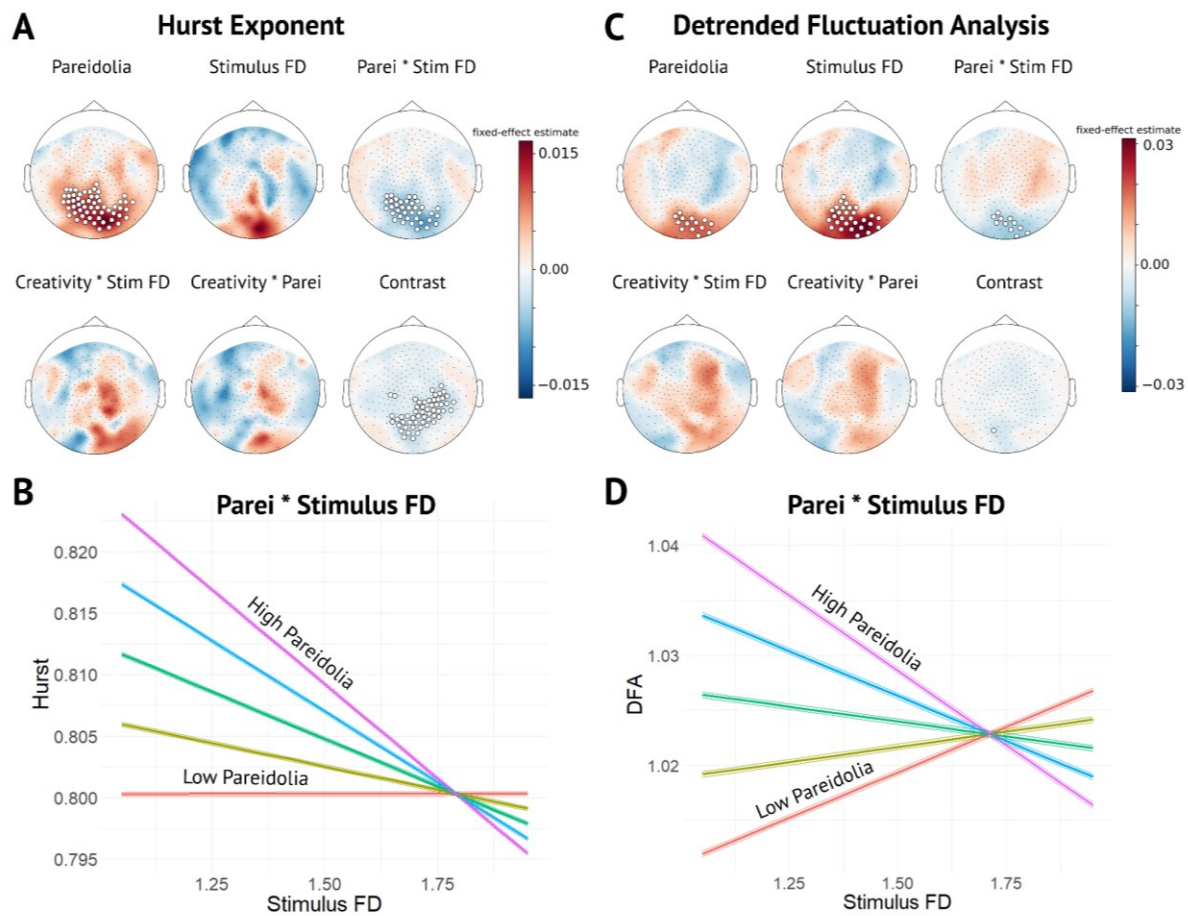


Figure 3.5. Predicting brain long-range temporal correlation from stimulus fractality, pareidolia and creativity. (A) Fixed effects and interaction terms of Hurst Exponent predictors. (B) Predicted values of the interaction of pareidolia and stimulus fractality in predicting Hurst Exponent, averaged across significant sensors. (C) Fixed effects and interaction terms of DFA predictors. (D) Predicted values of the interaction of pareidolia and stimulus fractality in predicting DFA, averaged across significant sensors. White dots in the topographic maps indicate statistically significant regions ($p < .05$ after FDR correction). $N_{obs} = 2687$.

The effect of pareidolia and creativity on spontaneous brain complexity

To investigate the effect of the pareidolia task on spontaneous brain activity we compared resting state (RS) activity before and after the task for periods of 3 minutes. We built a mixed-effect model with a binomial outcome (pre vs. post), using brain metrics as predictors, as well as their interactions with the averaged pareidolia occurrences during the task, and individual creativity scores (refer to **Fig. 3.6A** and **Table S3.1**). In the post-task resting state, our analysis identified a significant decrease in theta and low-beta spectral power, coupled with an increase in alpha power, predominantly in the occipital and parietal regions. Concurrently, a notable decline in occipital gamma power, particularly in the 60-90Hz range, and a reduction in central high-beta activity were observed. Moreover, there was a general rise in LZC across the brain. Distinct changes in brain activity were linked to different levels of pareidolia occurrences during the task and individual creativity scores (see **Fig. 3.6B**). Participants with high pareidolia levels exhibited inverse trends in the aforementioned fixed effects, as illustrated in **Figure 3.6A**'s second row. Similar patterns were seen in highly creative individuals, who displayed increased occipital low-beta and gamma1 activity. Moreover, those with high creativity scores showed a slight widespread decrease in high-gamma band activity, while participants with lower creativity experienced a substantial global increase in this band. Additionally, high-creative individuals demonstrated a more pronounced rise in theta activity and a lesser increase in LZC compared to their low-creative counterparts. The three-way interactions, detailed in the fourth row of **Figure 3.6A**, reveal that pareidolia levels experienced during the task influence spontaneous brain patterns differently in high- and low-creative individuals. This effect is predominantly observed in the occipital regions across multiple frequency bands and more broadly in the brain for the high-gamma band. Notably, this triple interaction presents differential patterns between anterior and posterior brain regions for LZC. We evaluated the slope of the aperiodic component for the 3 minutes of resting state across all sensors and participants. This analysis revealed a consistent decrease in exponent

values within the right hemisphere post-pareidolia task, as demonstrated in the topological distribution of **Figure 3.6C**. Additionally, the overall scalp distribution of exponents was found to be significantly lower in post-task resting state ($t = 18.56$, $p = 4.6e-50$, $df = 269$). Furthermore, employing a random forest multi-feature classifier, we achieved a decoding accuracy of 65% on single-trial assessments. Notably, LZC and high-gamma (60-90Hz) emerged as the features contributing the most to the classification across all sensors (see **Fig. 3.6D**).

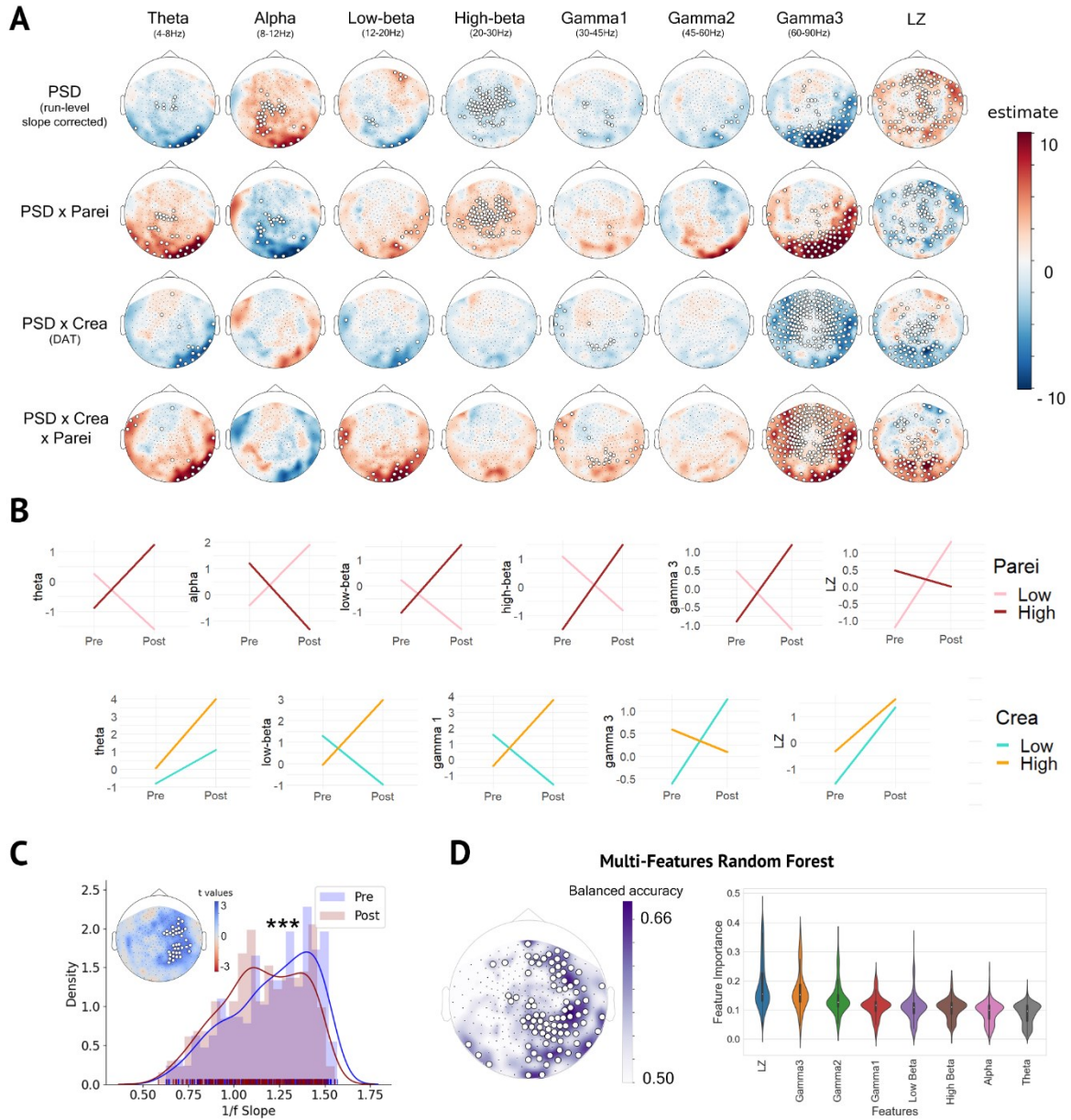


Figure 3.6. Multivariate analysis of resting state activity before and after the pareidolia task. (A) Predictive modeling of pre- and post-pareidolia task resting state. Topographic maps indicate fixed effect estimates for PSD and LZ (first row), and their interactions with pareidolia (second row), creativity score (third row), as well as the triple interactions (fourth row). White dots in the topographic maps indicate statistically significant regions ($p < .01$ after FDR correction) $N_{obs} = 1397$. **(B)** Interaction graphs showing the relationships between brain metrics and the average frequency of pareidolia (top row) and creativity scores (bottom row). These graphs are based on the mean predictions from models of significant sensors. Categories for low and high levels of pareidolia and creativity were determined using the lower 10% and upper 90% quantiles, respectively. Average predicted values are calculated for pre- and post-task periods, with thresholds set at 0.3 for pre-task and 0.7 for post-task. **(C)** Distribution of the 1/f slope exponent across all sensors (***: $p < .01$). Topological distribution representing significant sensors ($p < .05$, uncorrected for multiple comparisons). **(D) Left panel:** Topographic distribution of balanced accuracy in predicting pareidolia using a multi-feature Random Forest model. White dots on topographic maps represent sensors with statistically significant fixed effects ($p < .001$ after maximum statistics correction using 1000 permutations). **Right panel:** Violin plots representing the distribution of feature importance across different predictors, with LZC and Gamma3 showing the highest values.

The effect of perceptual placebo on pareidolia

Participants who underwent the final two bonus blocks were exposed to a perceptual placebo condition. They were informed that an artificial intelligence algorithm had analyzed their initial responses to fractal images and would aim to either amplify or diminish their pareidolia experiences in two subsequent blocks. This strategy was designed to evaluate how suggestion affects the perception of ambiguous stimuli.

Results revealed a discernible impact of the perceptual placebo on pareidolia occurrences. Under the 'up' condition, purportedly designed to enhance pareidolia, participants exhibited a significant increase in pareidolia percentages compared to the 'down' condition ($t(7) = 4.612, p = 0.002, d = 1.630$), which was intended to suppress pareidolia (see **Fig. 3.7C**). Furthermore, the distribution of the number of percepts reported by participants showed a marked difference between the 'down' and 'up' conditions ($t(7) = 2.441, p = 0.045, d = 0.863$), with a notably higher number of percepts in the 'up' condition (see **Fig. 3.7D**).

The mixed effect models revealed a significant interaction between the sham conditions and creativity levels in predicting the number of percepts ($\beta = 0.079, SE = 0.027, z = 2.950, p = 0.003$, see **Fig. 3.7F**) and a not significant interaction when predicting pareidolia occurrences ($\beta = 0.07, SE = 0.05, z = 1.55, p = 0.12$, see **Fig. 3.7E**). The significant interaction suggests that the effect of suggestion on pareidolia varies depending on the level of creativity. Specifically, this finding implies that individuals with higher creativity levels experience a more pronounced difference in pareidolia response between the up and down sham conditions compared to those with lower creativity levels. These results substantiate the hypothesis that suggestion can effectively modulate perceptual experiences and that this modulation is contingent upon the creativity levels of individuals. The findings underscore the malleability of perception under the influence of expectation and suggest that creative thinking may predispose individuals to heightened sensitivity to such suggestive effects.

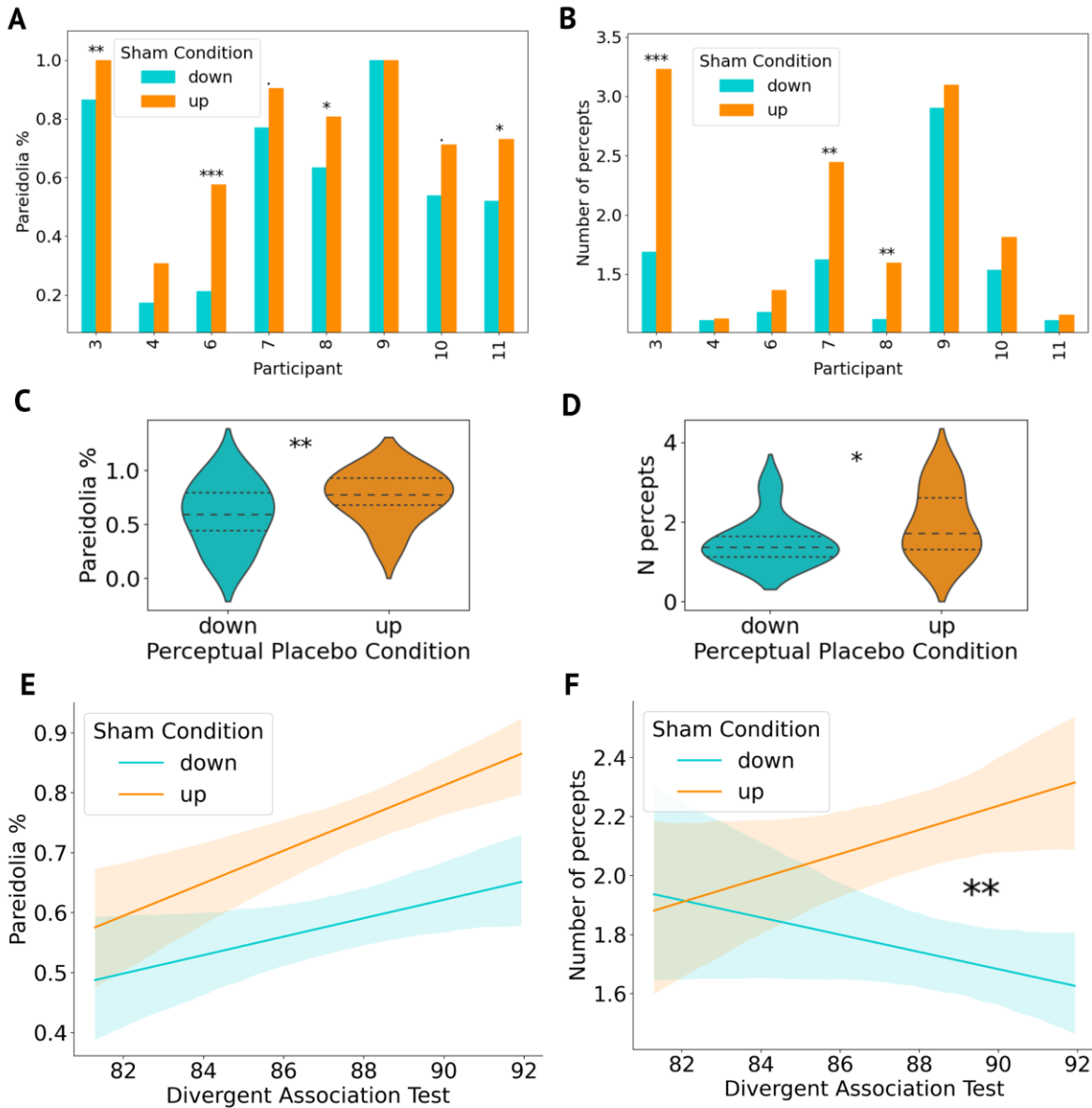


Figure 3.7. Effect of perceptual placebo on pareidolia and its interaction with creativity. (A) Averaged pareidolia occurrences for each participant under 'down' and 'up' blocks sham conditions, showing a variable response between 'down' and 'up' blocks. (B) Number of percepts per participant under sham conditions, also showing variability with some significant differences indicated by asterisks. (C) Pareidolia % distribution across perceptual placebo conditions 'down' and 'up', with a significant difference denoted by double asterisks. (D) Distribution of the number of percepts in the perceptual placebo condition, with a notable difference between 'down' and 'up'. (E, F) Interaction between creativity scores and sham conditions in predicting pareidolia occurrences ($N_{obs} = 832$) and number of percepts ($N_{obs} = 559$). Asterisks denote levels of significance (* $p < .05$, ** $p < .01$, *** $p < .001$), $N_{subj} = 8$.

Discussion

The overarching goal of this study was to probe the neural markers of divergent perception, particularly focusing on the interplay between creativity and the complexity of visual stimuli in pareidolia. Our approach leveraged fractal images to provoke pareidolic experiences, thereby offering a unique window into the neural processes underpinning the recognition of patterns in ambiguous visuals.

Our observations underscore that pareidolia engages a spectrum of neural mechanisms, evidenced by changes in theta and alpha brain oscillations, which extend beyond the traditionally emphasized gamma activity. This finding suggests the activation of diverse neural pathways in the recognition of patterns within ambiguous stimuli. Notably, the present study reveals that individual creativity levels play a significant role in modulating these neural responses, underlining the impact of personal cognitive styles on perceptual processing. Furthermore, our results demonstrate that brain patterns during spontaneous pareidolia differ from those observed in deliberate or delayed manifestations of the phenomenon, suggesting unique cognitive and neural underpinnings for spontaneous pattern recognition. In addition, our research brings to light the phenomenon of fractality matching. Here, the complexity of brain signals, particularly in occipital areas, exhibits an inverse relationship with the complexity of visual stimuli, a pattern that shifts to a positive correlation with the fluency of spontaneous pareidolic experiences. Additionally, our findings reveal a general shift in brain activity patterns post-task, predominantly in the occipital region. These changes, encompassing power spectral density, complexity, and aperiodic components, are significantly modulated by individual differences in pareidolia occurrences and creativity levels, underscoring the complex interplay between perceptual experiences and cognitive traits. Lastly, the study sheds light on the sensitivity of creative individuals to perceptual placebo, suggesting that creativity might predispose individuals to a heightened response to suggestive influences in perception.

Pareidolia onset is associated with changes in oscillatory power, scale-invariance and signal complexity

In the literature on perceptual binding, gamma oscillations have been widely recognized as critical for integrating sensory information into coherent percepts (Fries, 2009; Tallon-Baudry & Bertrand, 1999). However, our results suggest that other oscillatory mechanisms, possibly involving lower frequency bands, might also play significant roles in unconstrained pareidolia, which involves more processes than perceptual binding processes, such as active visual search and imagination. Interestingly, emerging perspectives challenge the exclusivity of gamma band activity in perceptual binding and highlight the causal role of theta and beta oscillations (Ghiani et al., 2021). The observed changes in alpha and theta bands could indicate alternative neural pathways engaged during pareidolia, which might be involved in the initial stages of pattern recognition or in maintaining a balance between internal representations and external sensory inputs. Past studies have linked frontal theta activity to cognitive control and immersion in the task (Cavanagh & Frank, 2014; Katahira et al., 2018), suggesting a central role in working memory crucial for coordination of multiple cognitive processes (Sauseng et al., 2010). Moreover, increased frontal theta power has been associated with proactive perceptual switching (López et al., 2019; Nakatani & Leeuwen, 2005) and illusory visual perception during presentation of ambiguous stimuli (Mathes et al., 2014). Interestingly, it has been shown that variations in frontal theta are directly correlated with the degree of perceptual uncertainty (Maksimenko et al., 2020), with more pronounced variations in individuals who leverage uncertainty as a strategy for exploration (Cavanagh et al., 2012). The observed decrease in frontal alpha power associated with pareidolic experience aligns with prior findings in the field of multistable visual perception. This includes evidence of perceptual destabilization preceding a change in visual awareness of ambiguous motion, as shown using magnetoencephalography (MEG) (Strüber & Herrmann, 2002). Additionally, similar reductions in alpha power have been reported during perceptual switches in an experiment using Necker Cube stimuli (Sangiuliano Intra et al., 2018). Collectively,

these findings suggest a consistent association between decreased alpha power and the perception of ambiguous or shifting visual stimuli, aligning with the concept of a bottom-up figure reversal mechanism. Recent research has explored the specific delineation of frequency bands concerning perceptual content and stability. In this framework, the encoding of perceptual content is linked to the raw fluctuations in low-frequency components (below 5Hz), while perceptual stability is predominantly affected by the amplitude fluctuations in alpha and beta oscillations (Hardstone et al., 2022). Consequently, the observed elevation in theta power may be more indicative of the emergence of perceptual content rather than its stability. Furthermore, the interaction between creativity levels and gamma oscillatory activity highlights the variability in neural processing during pareidolia across individuals, with differences attributed to their respective levels of creativity. Indeed, in individuals with high creativity, the observed increase in gamma activity within central regions, responsible for the integration of complex sensory information, could indicate a reliance on associative sensory networks for creating pareidolic perceptions. This finding is consistent with literature suggesting that creativity traits influence perceptual experiences and their associated neural responses (Dietrich & Kanso, 2010).

We also observed an increase in LZC in the frontal areas during the onset of pareidolic perceptions. However, this finding should be interpreted cautiously, as the significant effects were primarily detected in the first row of sensors, potentially indicating an influence from ocular movements. This said, we ran additional analyses where we computed LZC directly from the EOG signals and found no significant difference in LZC between pareidolia and non-pareidolia trials. The association of increased LZC with the attribution of meaning to visual stimuli (Orłowski & Bola, 2023) aligns well with pareidolia, which involves discerning meaningful patterns in otherwise ambiguous visual stimuli. Additionally, we observed a reduction in the slope of the aperiodic component, predominantly in the left hemisphere, coinciding with the emergence of pareidolic percepts. Recent interpretations propose that the M/EEG spectrum's slope, when plotted on a

log-log scale, serves as a gauge for the neural excitation/inhibition (E:I) balance (Ahmad et al., 2022; Gao et al., 2017; Waschke et al., 2021, 2019). Here, lower values, which indicate a flattening of the slope, are interpreted as a rise in the excitation/inhibition ratio—either through an increase in excitation, a decrease in inhibition, or both—resulting in greater complexity of brain dynamics. Moreover, EEG spectral exponents are known to track modality-specific, attention-induced changes in E:I, with flattening of EEG spectra associated with selective allocation of attentional resources (Waschke et al., 2021). Hence, the observed decrease in the 1/f spectral slope during pareidolia, especially lateralized to the right hemisphere, suggests a shift towards reduced inhibition in the brain's neural dynamics, potentially facilitating the emergence of pareidolic perceptions by allocating attentional resources more selectively. This alteration potentially facilitates the emergence of pareidolic perceptions, through an increase in aberrant salience, reflecting a heightened attribution of significance to ordinary stimuli.

Spontaneous pareidolia is characterized by distinct oscillatory dynamics

To further understand the mechanisms underlying unconstrained pareidolia, we aimed to delineate the neural dynamics by computing MEG spectral power and LZC separately for early (i.e. spontaneous) and late (voluntary) pareidolia. Contrasting these two conditions revealed significant differences in brain activity patterns which were particularly marked by increased theta and beta power, decreased LZC, as well as decreased central alpha during early pareidolia. These findings suggest that the rather earlier bottom-up and effortlessly occurring pareidolia is mediated by neural processes that are at least in part different from those that support a more effortful voluntary form of pareidolia. In particular, the observed increase in occipital theta during spontaneous pareidolia may suggest a potential link between the emotional aspects of pareidolia and the recognition of ambiguous visual information (Uusberg et al., 2014). A decrease in central alpha, indicative of reduced neural inhibition, has been associated with increased excitability and improved performance in detecting near-threshold visual stimuli, possibly playing a role in the

heightened perceptual sensitivity during early pareidolia (Ergenoglu et al., 2004). Moreover, alpha oscillations are known to be modulated by bottom-up factors such as the presence of salient stimuli, which in turn affects the activity in regions responsible for processing visual information (Nelli et al., 2021; Woertz et al., 2004). Interestingly, alpha synchronization seems more pronounced in tasks requiring intensive internal processing and top-down control, compared to those dominated by bottom-up processing, implying that spontaneous pareidolia may hinge on bottom-up mechanisms, potentially indicative of a pop-out effect (Benedek et al., 2011). In the context of processing ambiguous stimuli, an increase in beta activity has been associated with an early and spontaneous phase of disambiguation, a neural response that could be integral to the initial stages of pareidolia (Maksimenko et al., 2020). This is complemented by findings that suggest an increase in beta activity is also associated with endogenously-driven perceptual reversals, hinting at the role of beta oscillations in the cognitive processing required for interpreting ambiguous visual inputs (Kornmeier & Bach, 2012). On the other hand, beta desynchronization has been linked with the disambiguation of hidden figures, which could be indicative of the neural mechanisms that facilitate the resolution of visual ambiguity in pareidolia (Minami et al., 2014). This contradictory aspect implies that while increased beta activity might be associated with the initial recognition and interpretation of ambiguous stimuli, beta desynchronization might play a role in the subsequent resolution and clarification of these stimuli. The elevation of occipital high-gamma activity in early pareidolia suggests a heightened state of neural processing specific to the initial stages of recognizing ambiguous visual stimuli. High-gamma activity, particularly in the occipital region which is integral to visual processing, is often associated with the rapid and efficient binding of visual features into coherent perceptual entities (Castelhano et al., 2013; Ding et al., 2017; Ghiani et al., 2021). This process likely involves the activation of higher-order visual areas that work to integrate disparate elements, facilitating the quick emergence of recognizable patterns or shapes from ambiguous scenes (Ding et al., 2017; Rodriguez et al., 1999).

Earlier instances of pareidolia appear to be associated with less complex neural patterns, as indicated by lower levels of LZC, compared to the richer, longer-lasting and arguably more effortful visual search for meaningful forms later in the trial. Thus, pareidolia that develops over a longer period of visual inspection may be associated with richer neural patterns, reflecting an increased attribution of meaning to the stimuli (Orłowski & Bola, 2023). The observed increase in the slope of the aperiodic component in central regions during spontaneous pareidolia trials suggests an increase of the E:I ratio, possibly indicative of a more focused and regulated approach in processing pareidolic images. This could reflect a neurophysiological strategy in key areas like the parietal and motor regions to enhance filtering and processing efficiency, thereby refining perception and stabilizing the interpretation of ambiguous visual stimuli.

Fractality matching is modulated by pareidolia fluency

Given that both the ambiguous visual stimuli and the recorded neuromagnetic activity exhibit fractal properties, and in light of prior research in this domain (Carpentier, 2020; Waschke et al., 2021, 2019), it seemed compelling to investigate the potential relationship between the fractal dimension of the stimuli and the fractal characteristics of the neural responses they elicited. This phenomenon, known as complexity matching, posits a linear relationship between external stimuli and neural complexity (Carpentier, 2020). Our investigation focused on a slightly different, though intricately related, version of this concept, which we refer to as fractality matching. Recent research employing a disk with changing luminance based on various $1/f$ exponents has demonstrated that EEG spectral exponents mirror the spectral exponent of the visual stimulus, particularly in visual regions (Waschke et al., 2021). Nonetheless, there appears to be no existing study that has examined the connection between visual fractal stimuli and corresponding fractal patterns in brain activity.

To target this relation, we assessed self-similarity of brain signals and its correlations over different timescales using Detrended Fluctuations Analysis and Hurst exponent. We discovered

that in occipital regions, DFA rises when the fractal dimension of the stimulus decreases. This inverse fractality matching becomes particularly intriguing when considering its interaction with pareidolia, as evidenced by both DFA and Hurst Exponent analyses, revealing that a high incidence of pareidolic perceptions shifts the fractality matching to a positive correlation. In other words, when individuals reported a higher frequency of pareidolic experiences, the complexity of the brain signals mirrored the complexity of the stimuli more closely. Our results confirm that multiple measures of brain fractality in occipital regions relate to the fractal dimension of visual stimuli. Notably, this relationship was modulated by pareidolia in metrics assessing signal persistence and memory (Hurst exponent, DFA), whereas metrics primarily associated with irregularity and complexity (Sevcik and Petrosian) did not exhibit this modulation (see **Fig. S3.1**).

Importantly, our results are in line with studies showing that complexity matching is intimately linked to perceptual processes (Carpentier, 2020) and that EEG spectral exponents track $1/f$ features of visual stimuli during a visual perception task (Waschke et al., 2021). Building upon this research, our findings suggest a dynamic interplay in which pareidolia enhances the brain's capacity to align its internal patterns with those of the external stimulus. Our observations are consistent with a contemporary model of brain fractality proposing that external stimuli may constrain scale-free dynamics within the brain (Grosu et al., 2023). This adaptability might be a fundamental characteristic of neural computation, enhancing the brain's capacity for efficient information processing and participating in altered perceptual processes. Such findings suggest that the brain's adaptability in dealing with information is rooted in its inherent scale-free nature, which is essential for dynamic and efficient neural computation (Ribeiro et al., 2021; Stoll, 2024).

Our findings also reveal a significant correlation between the frequency of pareidolic percepts and both the Hurst exponent and DFA, predominantly in the occipital regions. This suggests that during pareidolic experiences, these regions may amplify their intrinsic scale-free dynamics, exhibiting enhanced self-similarity and memory-like qualities in the signal. These

observations contribute to the expanding evidence that the brain's fractal dynamics can be modulated by complex cognitive demands and specialized expertise, such as those involved in the perception and mental visualization of art (Karkare et al., 2009). Such modulation reflects the adaptability of brain activity in response to perceptual tasks that require a high degree of creativity and imagination, as is the case with pareidolia.

Engagement with a pareidolia task affects subsequent brain signal complexity

Our comparison of resting state data recorded before and after completing the pareidolia experiment sheds new light on how pareidolia and creativity shape brain dynamics. First, we found that engaging in a pareidolia task significantly alters the spontaneous activity of the brain, consistent with previous studies showing changes in resting brain activity during post-encoding phases of visual stimuli, both in EEG (D’Croz-Baron et al., 2021; Moissello et al., 2013) and fMRI (Guidotti et al., 2015; Wang et al., 2012). In particular, we found evidence of task-related changes across theta, alpha, beta, and gamma bands, and in LZC, characterized by an increase in alpha band activity and LZC, and a decrease in the remaining frequencies. Specifically, there was a notable decrease in occipital gamma activity, alongside an increase in alpha power post-task. These changes may signify neural fatigue and heightened inhibition within the visual system due to the task’s demanding nature. The observed alterations were further dependent on the intensity of pareidolia experienced during the task and the creativity levels of the participants. Intriguingly, when participants experienced high levels of pareidolia, these effects were reversed, irrespective of individual levels of creativity. This suggests that diminished endogenous activity in visual areas post-task could be attributed to engaging in the task without perceiving pareidolic images. This scenario likely led to participants exerting more effort and actively searching for meaningful images, consequently exhausting their visual system more rapidly.

The significant increase in LZC post-pareidolia task, particularly among individuals with lower creativity scores, aligns with previous research suggesting that spontaneous brain activity

is not merely a passive state but is influenced by recent cognitive activities (Raichle, 2015). The heightened LZC observed post-task could reflect a state of increased neural readiness or adaptability in response to the cognitive demands of the pareidolia task (M. D. Fox et al., 2007). Studies have shown that psychedelic states, characterized by altered perceptual experiences, are associated with increased neural signal diversity, as measured by LZC (Farnes et al., 2020; Mediano et al., 2020; Schwartzman et al., 2019; Timmermann et al., 2019, 2023). This similarity hints at a possibility of a shared neural mechanism underlying the processing of complex perceptual experiences, whether induced by cognitive tasks like pareidolia or pharmacological agents like psychedelics. This suggests that the stimulation of pareidolia could potentially be leveraged to simulate altered perceptual experiences, akin to those observed in psychedelic states.

Notably, the three-way interaction between pareidolia, creativity and brain activity indicates that the effect of pareidolic experience on spontaneous brain patterns diverges for individuals with high and low creativity scores. This divergence suggests that these two groups may employ distinct cognitive strategies when experiencing pareidolia. This differential engagement not only reflects in the varying levels of brain complexity post-task but also in the distinct spectral patterns observed in the occipital region, where significant changes in theta, alpha, and gamma activities are evident. Individuals with lower creativity scores exhibited a notable increase in LZC post-task, which could be interpreted as a compensatory neural mechanism, where less creative individuals require greater neural complexity to process ambiguous images and actively search for novel perceptual experiences. This finding resonates with the concept of neural efficiency, where the brain optimizes its resource allocation in response to task demands (Neubauer & Fink, 2009). This nuanced understanding of how creativity influences the brain's response to pareidolia enriches our comprehension of the neural underpinnings of perception and imagination. It opens up new avenues for exploring how

perception of ambiguous stimuli, as well as cognitive traits like creativity shape individual brain dynamics in the resting brain.

Creative individuals are more sensitive to perceptual placebo

To explore the impact of suggestion on pareidolia, we implemented a sham condition in which participants were led to believe that an AI algorithm was manipulating the task's difficulty based on their brain responses. This design is informed by prior studies employing a mock brain scanner, demonstrating how neuro-hype alters participants' belief in improbable statements, a phenomenon termed neuroenchantment (Ali et al., 2014). In the present study, participants reported increased pareidolia under the 'up' sham condition, which aimed to boost pareidolia experiences, in contrast to the 'down' condition meant to reduce them. The differential response to suggestion across creativity levels indicates a cognitive predisposition to suggestion in individuals with higher creativity, aligning with studies reporting enhanced suggestibility in more creative and hypnotizable subjects (Ashton & McDonald, 1985; Bowers, 1978). Furthermore, creative individuals tend to experience fantasy proneness more easily (Lynn & Rhue, 1986), which might be associated with their tendency to report higher levels of pareidolia during the 'up' sham condition. These results support the concept that perception is highly modulated by top-down cognitive elements, including beliefs and expectations, contributing to the discourse on how cognitive styles, like creativity, influence perceptual processes. It underscores the importance of further investigating the cognitive mechanisms that modulate sensory experiences, particularly in the context of therapeutic and clinical settings where suggestibility can be a valuable tool.

Limitations and Future Directions

Our study, involving twelve neurotypical individuals, faces limitations due to its relatively small sample size, which might impact the generalizability of our findings. The limitation was mitigated by employing generalized linear mixed-effect models, which capitalized on the high

number of trials per participant, thus maintaining statistical power without necessitating averaging, as evidenced by the robust effect sizes observed. Moreover, the accuracy of our machine learning analysis, particularly highlighted in the leave-one-subject-out (LOSO) cross-validation, further supports the generalizability of our results. Secondly, the current design of our pareidolia task did not allow for a clear distinction between parallel and sequential pareidolia processes. Future research could benefit from task modifications that enable differentiation between these processes, such as instructing participants to either maintain the first percept when identifying subsequent ones for parallel processing or systematically dissolve the first percept before recognizing the next one for sequential processing. Additionally, the potential influence of mental imagery on pareidolia was not explicitly considered in our study. Mental imagery capabilities may significantly impact how participants perceive and interpret fractal images. Subsequent studies could integrate assessments or control measures for mental imagery to enhance our understanding of its influence on pareidolia and associated neural mechanisms.

To gain a more holistic understanding of pareidolia, future research could extend to auditory pareidolia, which would help explore trans-modal mechanisms of how the brain constructs meaningful percepts from ambiguous stimuli. Moreover, the potential of generative models, like diffusion models, in creating diverse types of ambiguous images presents an exciting avenue for future pareidolia research. Exploring a broader range of stimuli could provide novel insights into the neural correlates of pareidolia and enhance our understanding of altered perceptual processes in both humans and machines.

Conclusion

This study investigated the neural markers of divergent perception, using an unconstrained pareidolia paradigm in which individuals had to detect meaningful objects in generated fractal images. The examination of oscillatory dynamics, complexity metrics, and

fractality metrics offers a multifaceted perspective on the pareidolic brain, providing critical insights into how variations in creativity levels shape brain dynamics during pareidolia. Our study reveals that different oscillatory patterns across multiple brain frequencies are associated with pareidolia, challenging the traditional focus on gamma band activity in perceptual binding. The changes observed in aperiodic components hints towards an alteration of the excitation/inhibition balance during pareidolic experience, while the alterations in LZC might reflect phenomenological changes related to the richness of the perceptual content. Furthermore, the meticulous control of stimulus fractality levels enables a deeper understanding of the coupling between endogenous (brain) and exogenous (stimulus) self-similarity properties. Crucially, we found that fractality matching between brain signals and visual stimuli is modulated by pareidolia fluency, indicating that altered perception influences the link between neural activity and the properties of external stimuli. This interplay offers valuable insights into how altered perceptual processes are related to the properties of sensory input. Additionally, we demonstrated that creativity levels interact with how the brain processes and makes sense of ambiguous stimuli. Our findings illustrate how the balance of bottom-up and top-down processes in perception is modulated by individual creativity levels, shedding light on the complex interplay between internal cognitive states and sensory experiences in the creative brain. This nuanced understanding underscores the significant influence of creativity on the neural mechanisms governing perception and interpretation of ambiguous stimuli. These findings deepen our understanding of sensory integration and highlight the complex interplay between creativity and sensory perception.

The harmonicity of brain dynamics: a neurophenomenological approach to creative biofeedback

Abstract

This chapter delves into the potential parallels in harmonicity between brain signals and music, exploring the nature of these similarities and their implications. We review research that manifests contribution to such joint endeavors. Notably, the Binary Hierarchy Brain Body Oscillation Theory and the General Resonance Theory of Consciousness suggest that biological systems depend on harmony and resonance to communicate and facilitate integrative functions. Based on various findings pertaining to both brain and music (such as the neural model of consonance), we argue that dynamic musical systems could benefit from harmonic analysis of biological activity. We show that brain signals exhibit harmonic properties that can be measured as the arithmetic ratios of their spectral peaks - which is referred to as stationary harmony in music theory, and harmonic architecture in neuroscience. Along with this exploratory data analysis, we assess how current M/EEG signal processing techniques relate to methods accounting for harmony. On this ground, we extend the concept of transitional harmony (Chan et al., 2019a) to brain signals to analyze the temporal unfolding of spectral peaks and their relative proportion. We suggest that these multiscale temporal properties can characterize trajectories of states of consciousness, especially in the case of brain-computer interfaces, through dynamically matching the harmonic architecture of brain dynamics with congruent auditory feedback. We present new sonification methods of bioharmonicity, allowing for dynamical tuning construction and identification of spectral chords. We argue that these tools offer a compelling case of modeling brain dynamical transitions that reflect and alter phenomenology. In sum, the fluid circulation between first- and third-person observations allowed by such interface provides a generative passage (Lutz, 2002; Roy et al., 1999) in that it widens our understanding of subjective experiences as much as their underlying biological processes. We share our ideas for potential artistic applications as well as experimental protocols and models that we think are best suited to study resonance and harmonicity in human-machine interactions.

1. Introduction

Pythagoras, correlating musical pitch with the length of a vibrating string, initiated a tradition of employing mathematics to interpret the natural world, extending it to study celestial bodies' movements (Cartwright et al., 2021). For Pythagoreans, harmony (i.e. simple integer ratios) is a property of any natural system that tends to order. Building on Pythagorean principles, research has uncovered harmonics in diverse phenomena such as ion motion (Joshi et al., 2020; Köster, 2009), electron wave functions (Schrödinger, 1926), DNA structures (Petoukhov et al., 2021), and vocal resonances (Lewicki, 2002; Qi & Hillman, 1997), illustrating the self-organizing capacities of biological entities (Guénin—Carlut, 2022; F. Varela et al., 2001).

Recognizing the prevalence of harmonics in diverse natural phenomena, it becomes imperative to consider the methodologies used to analyze harmonic structures in brain dynamics, as a way to both refine our scientific understanding of brain functioning and to explore bio-inspired musical structures. While Fourier/Hilbert Transform is pivotal in frequency-domain analysis (Motamedi-Fakhr et al., 2014), their typical applications often neglect a detailed examination of the signal's harmonic structures, potentially forgoing insights into the emergent properties of brain dynamics. A more discerning approach to frequency-domain analysis enables the uncovering of these harmonic components by scrutinizing the organization of spectral peaks within brain signals.

In line with this approach, this chapter synthesizes musical and scientific insights of oscillatory phenomena to formulate a theoretical foundation for musical systems that harness biosignals' harmonic structures in the design of creative Brain-Computer Interfaces (BCI). In doing so, we aim to address the following questions:

1. What are the prevalent computational models of harmonicity and tuning systems (sections 2 to 4)?
2. What is the functional role of nested harmonic structures in brain dynamics (section 5)?
3. How can harmony of brain dynamics be translated into musical systems (sections 6 and 7)?
4. How can BCIs be used to expand both states of consciousness and musical structures through the modeling of biosignals' stationary and transitional harmony (Chan et al., 2019a) (section 8)?

We believe the answers we give to this set of questions might shed light on novel experimental methodologies in neuroscience borrowing from musical knowledge while inspiring new ways to experience music (as a listener or performer). Our endeavor does not center on uncovering universal brain aesthetics or delving into the nuances of neural organization influenced by cultural music. Instead, we align with a distinct phenomenological tradition, one that values insights from lived experience and employs innovative methodologies to explore its biological counterparts (Depraz & Desmidt, 2019; Lutz & Thompson, 2003; Ramstead, 2015; Ramstead et al., 2022; Roy et al., 1999; F. Varela et al., 2001). Consider, for instance, the ability to recognize a song without listening to it in its entirety; each note of its melody is perceived in context with its neighbors, highlighting the temporal depth of lived experience and illustrating how harmonicity conveys information across diverse timescales.

We provide tools that leverage the isomorphism (i.e., similarities in form) between the harmonic architectures of brain-body oscillations (HABBOs) and musical systems to investigate the constitution of (musical) lived experience. We consider the unfolding of these harmonic structures, termed as transitional harmony (Chan et al., 2019a), to probe how consonance and

dissonance vary within biological signals. We discuss modeling of such bioharmonicity, and how it could trigger phenomenologically meaningful changes in musical systems, within the context of brain-computer interfaces (BCIs).

Throughout the manuscript, we use a dataset of magnetoencephalographic (MEG; 270 channels) recordings from 11 participants that were asked to detect meaningful objects across a set of 320 ambiguous visual stimuli. This dataset serves solely as an illustrative example to demonstrate the application of various computational methodologies to M/EEG signals. The participants provided informed consent, and the study received approval from the relevant ethics board. It is important to note that the focus here is on the methodological exposition rather than on the empirical analysis or comparison of different experimental conditions. While the dataset provides a practical context for showcasing the methods, we refrain from any statistical interpretation of the task-specific data. Nonetheless, we acknowledge the potential of future research to systematically explore how metrics of harmonicity might inform our understanding of brain signals across different states of consciousness.

2. Computational models of consonance and dissonance

The idea of consonance in music traces back to ancient thinkers like Pythagoras, who postulated that the consonance of musical intervals is determined by the simplicity of their frequency ratios (Ferguson, 2011). This perspective posits that each musical note can be defined by its fundamental frequency, and the relationship between multiple notes is best captured by their ratios. Similarly, Euler proposed a system that grades chord aesthetics based on the least common multiple of the notes (Euler, 1739) while harmonicity of specific scales have been quantified using the averaged similarity between each pair of notes and the natural harmonic series (Gill & Purves, 2009a). From a simplified interval p/q , similar metrics of harmonicity can be derived, including the Tenney Height (logarithm of p^*q) (Deza & Deza, 2014), the sum of p and q , as well as the *sum-by-product* of p and q ($(p+q)/(p^*q)$).

Historically, two main schools of thought have shaped our understanding of harmony. The Pythagorean school emphasizes temporal features, deriving consonance from wavelength ratios. In contrast, the Helmholtzian school adopts a psychoacoustic lens, emphasizing spectral features. Helmholtz introduced the notion of beating frequencies, denoting the perceived amplitude modulations resulting from two closely spaced frequencies. As the modulation frequency increases, this perception leans towards discordance (Rasch, 1984). This spectral-based view not only delves into the psychophysics of harmony but also reveals how complex sound properties, such as interharmonic modulations, influence our perception of consonance and dissonance (Chan et al., 2019a).

Bridging these historically distinct viewpoints, Chan, Dong and Li (2019) offered a holistic model of harmony. Their approach encapsulates both stationary and transitional aspects of harmony through interharmonic and subharmonic modulations. Crucially, they demonstrated that such modulations could articulate both perceptual tension-resolution and computational harmony statistics, reconciling the Helmholtzian and Pythagorean paradigms. Their contributions pave the way for nuanced mathematical frameworks that compute tension trajectories within transitional harmony. Given that the patterns of tension and resolution in music can suggest possible transitions and musical movements, we extrapolate this concept to brain-body oscillations (HABBOs) by suggesting methods leveraging the tension-resolution patterns inherent in brain dynamics as a novel avenue for musical exploration.

3. The evolution of musical tuning systems

Musical tuning systems, which determine how an octave¹ can be divided into a set of frequency ratios, have evolved significantly over time. These systems have sought to balance the harmonicity of ratios with the practical requirements of musical performance.

3.1. Historical Systems and Their Limitations

The Pythagorean scale, one of the earliest systems, is rooted in a $3/2$ ratio known as the fifth. This system's foundation lies in expressing harmony through simple integer ratios in the form $2^q \cdot 3^p$ where p and q are integer ratios. A subsequent system, the just intonation, aimed to rectify the Pythagorean scale's complex frequency ratios, like the major third ($3^3/2^6$; $81/64$). By incorporating ratios in the form $2^q \cdot 3^p \cdot 5^r$, it replaced complex ratios with simpler ones, such as transforming the Pythagorean major third of $81/64$ to $5/4$ (Fauvel et al., 2003). However, these systems, predominant until the 18th century, faced a significant limitation: the inability to transpose or change the key within a composition. The equal-temperament tuning emerged as a solution, dividing the octave into equal steps. Each step is determined by the twelfth root of two ($2^{1/12}$) (Barbour, 1947). While this system facilitates transposition, it compromises the pitch accuracy of intervals.

3.2. Modern Computations and Dynamic Tunings

The advent of computers has revolutionized tuning. They offer the ability to dynamically adjust note frequencies based on the chosen key, ensuring precise interval justness without compromising transposition (Sethares, 1994, 2002). This computational power has also sparked innovative tuning constructions rooted in mathematical formalisms (Plamondon et al., 2009). Two particularly relevant methods for brain-music exploration include the dissonance curve and

¹ Not all tuning systems use the octave as the reference for repetition. An example is the Bohlen–Pierce scale, which instead uses a 3:1 ratio as its repetition point, dividing this range into steps with each frequency ratio being $3^{(i/13)}$.

harmonic tuning. It's worth noting that microtonality—a feature of these tunings—has been explored in various cultural contexts through different logical constructions (Ader, 2020; Benetos & Holzapfel, 2015; Werbock, 2011).

3.2.1. Dissonance curves

Sethares, in his seminal work "Tuning, Timbre, Spectrum, Scale", delves into the relationship between timbre and scale (Sethares, 2005b). Timbre, which characterizes a sound's unique quality, can be articulated by the amplitude and positioning of its constitutive harmonics. The dissonance curve, inspired by Helmholtz's beating frequencies concept, captures perceived dissonance across frequency ratios by accounting for a sound's spectral peak relationships, allowing a match between the structure of a timbre and a corresponding tuning. Take, for example, a flute note. It has a harmonic spectrum, and its corresponding dissonance curve reflects simple, harmonious ratios. In contrast, a bell's inharmonic spectrum yields a curve with complex ratios, mirroring its intricate timbre. This method allows seemingly dissonant intervals to be perceptually consonant when aligned with a compatible inharmonic timbre, enabling the creation of dynamic, harmonically resonant tunings tailored to individual timbres. Since timbre depicts the harmonic relations in a complex signal, we consider the dissonance curve as a powerful tool to develop adaptive tuning systems from brain signals.

3.2.2. (Sub)harmonic tunings

Harmonic tunings are formed by establishing a set of frequency ratios within the unison (1:1) and octave (2:1) range, originating from a sequence of harmonic positions. This involves adapting the original ratio of each harmonic, for instance, 3:1 for the third harmonic and 5:1 for the fifth, by dividing by 2^n octaves to confine the ratios within the 1:1 and 2:1 range. This process naturally reveals the simple ratios intrinsic to classical tunings, as the harmonic series inherently encapsulates these ratios within various octaves. The 8th Octave Overtone Tuning (Reinhard,

2011) exemplifies this, incorporating 128 unique pitch classes represented by the first 128 harmonics across 8 octaves.

We have outlined two methods for the construction of tunings that utilize spectral peaks and harmonic positions. These tunings, informed by the harmonic components found in biological signals like EEG, can establish a practical connection between musical expression and inherent biological rhythms. The application of these methods to brain signals will be further elaborated in Section 7.2.

4. Unveiling musical structure in dynamical systems

Before discussing the investigation of harmonicity in brain dynamics in Section 5, it's crucial to acknowledge prior efforts to explore the potential of dynamical systems in constructing musical systems. Recent advancements have revealed new musical structures by exploring systems of generative music and theories based on the behaviors of non-linear dynamical systems.

Bell & Gabora (2016) pioneered a generative musical algorithm designed to operate “at the edge of chaos,” embracing emergent behaviors. This project underscored the potential of algorithms employing hierarchical scale-free topology to yield outputs rich in creative potential. Given that varying musical genres exhibit scale-free behaviors (Levitin et al., 2012b), exploring emergent music in self-organizing systems stands to unearth new musical genres.

Further, another conceptual framework for algorithmic composition stemming from complex systems is ecosystem-based generative music (Bown, 2009). This approach aims to “yield complex outputs that are simultaneously intriguing to, and beyond the comprehension of, the user.” Dahlstedt (2009) introduced meta-generative methods dependent on evolutionary

algorithms to navigate complex aesthetics, advocating for utilizing the statistical properties of a system over time, such as complexity measures, to imbue both structure and dynamics.

Integrating a biological perspective, Project Santiago merges realistic neuron models with interactive music generation, where individual neuron activities modulate the musical outcome. This integration fosters intricate interactions across scales, ensuring a cohesive interplay between each musical parameter and sound event (Kerleñevich et al., 2011).

While these groundbreaking developments in generative music have broadened the horizons, our approach seeks to both enhance and build upon these foundations. We propose that biosignals, characterized by hierarchical scale-free behaviors, have the potential to guide and shape algorithmic musical systems. By mirroring the temporal evolution of the harmonic structures of these biosignals, our aspiration is to forge a distinctive blend between biology and musical expression. This convergence presents a novel outlook in the field of generative music by harmonizing biological rhythms with musical creativity.

5. Phenomenological and cognitive relevance of brain harmonicity

We've delved into the evolution of harmonicity in music and how the integration of temporality into theories of harmony enriches our understanding of musical perception. Additionally, we've showcased the innovative approaches of artists in developing musical instruments inspired by dynamical and adaptive systems. Given the brain's well-known dynamical complexity, we propose it as a fertile candidate for developing innovative biologically informed musical systems. As an intricate dynamical system, it showcases harmonies that relate to states of consciousness (Berkovich-Ohana & Glicksohn, 2014) and affective processes (Colombetti, 2013; F. J. Varela, 1999). HABBOs provide a lens, rooted in music theory, to interpret these brain harmonies.

We present evidence from the literature that supports the idea that brain dynamics can describe states of consciousness based on their harmonic architecture in the context of (1) auditory perception, (2) multiscale biological organization, and (3) resonance in complex systems (consciousness). Our aim is to emphasize that integrating the harmonic structures of brain dynamics into BCIs can potentially establish foundational insights into exploring the interconnection between phenomenology and brain dynamics through real-time feedback loops.

5.1. Neuronal model of consonance

To extract musically relevant features from HABBOS, it's imperative to understand how the brain processes auditory harmonicity and consonance. A neuronal model of consonance has recently been proposed, focusing on the role of the brainstem and primary auditory cortices in processing auditory stimuli (Bidelman & Krishnan, 2009; Lerud et al., 2014). This model aligns with recent findings that highlight the brain's sensitivity to musical pitch relationships (Fritz et al., 2009) and the encoding of consonant and dissonant intervals via phase synchronization between stimulus and frequency-following response (FFR) (Bidelman & Krishnan, 2009; K. M. Lee et al., 2015). Neural synchrony is essential in auditory processing (Boomsalter & Creel, 1961; Lots & Stone, 2008) and is known to reflect the periodicity of musical intervals (Fishman et al., 2001; McKinney et al., 2001; Tramo et al., 2001). Studies have demonstrated that consonant intervals, compared to dissonant ones, induce more periodic neural phase-locking (Bones et al., 2014; Langner, 1992). This suggests that our perception of consonance might stem from neural synchronization (Lots & Stone, 2008).

However, a pressing question arises: does the neural encoding of musical intervals merely mirror the acoustic properties of the stimulus, or are there non-linear modulatory processes at play? Addressing this, recent studies have shown nonlinear FFRs in the human brainstem and auditory cortex (Galbraith, 1994; K. M. Lee et al., 2009; Pandya & Krishnan, 2004; Purcell et al., 2007). These nonlinear sound transformations, carried out by neural encoding, are believed to

occur via mode-locking. Mode-locking is defined as an interaction between a periodic stimulus and a neural oscillation, resulting in $n:m$ locked oscillation cycles (Lerud et al., 2014).

Coherently, it has been suggested that “the explanation for consonance may lie in low-order integer frequency ratios, which is a fundamental principle of stability in oscillatory dynamical systems” (Lerud et al., 2014; Lots & Stone, 2008). Consonant and dissonant intervals predicted brainstem FFRs of both musician and non-musicians (K. M. Lee et al., 2009, 2015) by modeling mode-locked responses to stimulus frequencies, as well as to their harmonics and subharmonics. Interestingly, in this study, individuals with higher musical expertise showed increased nonlinearity in their encoding of musical intervals, which might reflect subjective properties associated with musical perception in experts.

Nonlinear encoding of musical intervals have also been explored by showing that perception of consonant intervals elicits more prominently the presence of common subharmonics in FFR, which was interpreted as a physical manifestation of the missing fundamental (K. M. Lee et al., 2015). It was also reported that more dissonant intervals lead to a higher number of nonlinear resonances in neural responses. Hence, the process of neural ‘filling-in’, associated with the auditory processing of ambiguous sounds, contributes to the illusory perception of the fundamental frequency, and to the richness of music perception. Therefore, the subharmonic profiles of brain-body oscillations might participate in the phenomenology of tension-resolution patterns in music (transitional harmony).

Collectively, these findings emphasize that musical consonance and dissonance are reflected in the brain via phase synchronization, mode-locking, and nonlinear resonances. This suggests that our perception of musical qualities is entwined with the brain's oscillatory behaviors. The interplay of frequencies in brain-body oscillations provides a window into both new musical structures and their experiential counterparts.

5.2. Harmonicity in Brain Dynamics: Challenge and Theories in Measuring States of Consciousness

Understanding the harmonicity in brain dynamics offers a unique perspective into how neural activity mirrors the harmonic structures of perceived sounds. We now explore theoretical and empirical works that study brain dynamics as harmonic relations between oscillators: the Binary Hierarchy Brain Body Oscillation theory and the General Resonance Theory of Consciousness (GRTC). Other established models of brain dynamics integrating the concept of harmonicity, such as harmonic brain modes (Atasoy, Deco, et al., 2018), stochastic resonance (Moss et al., 2004; Shukla & Bidelman, 2021), and echo state networks (Przyczyna et al., 2020), were considered but were deemed outside the scope of this chapter.

5.2.1. The Binary Hierarchy Brain-Body Oscillation Theory

The Binary Hierarchy Brain-Body Oscillation theory by (Klimesch, 2018a) serves as a pivotal framework, positing that phase synchronization and harmonicity are central to understanding the coordination of various human body systems across different timescales following a binary (2:1) frequency ratios structure. This theory hypothesizes that diverse frequency bands are integrally associated with different processing domains concerning cognitive and physiological functions, thereby minimizing spurious phase synchronization for non-harmonic ratios between frequency bands (Klimesch, 2013a).

To investigate the coordination of physiological systems further, computational tools like cross-frequency coupling (CFC) techniques have been key (Hyafil et al., 2015; Jensen & Colgin, 2007; Lisman & Idiart, 1995). Notably, a meticulous examination of CFC across the human brain using MEG demonstrated that widespread phase-amplitude coupling (PAC) is predominantly driven by harmonic signals (Giehl et al., 2021a). Cross-frequency phase synchrony (CFS), another type of CFC, is thought to “integrate, coordinate and regulate neuronal processing distributed into neuronal assemblies concurrently in multiple frequency bands” (Palva & Palva,

2018). It's crucial to discern that CFC between spectral peaks and their (sub)harmonics may be driven either by a single non-sinusoidal rhythmic process (i.e., spurious or ghost interactions) or the coupling of multiple physiologically separate harmonic oscillations (Giehl et al., 2021a). Recent methods have been developed to segregate genuine interactions and minimize these spurious interactions stemming from shared harmonic content (Idaji et al., 2022).

Expanding on Klimesch's theory, recent empirical findings align with the prediction that alert wakefulness is characterized by binary multiple frequency ratios, and sleep exhibits irrational frequency ratios between body oscillations (Rassi et al., 2019). The observed harmonic frequency ratios of heart rate, breathing, and alpha rhythm during varying consciousness states further corroborate these postulations. Moreover, binary frequency ratios have been identified in several conditions and tasks, emphasizing the importance of nested harmonic oscillations in maintaining homeostasis² and allostasis³ (Bartsch et al., 2007; Isler et al., 2008; Palva et al., 2005; Sauseng et al., 2008).

Klimesch (2018a) draws an interesting parallel between HABBOs and octave-based music, noting the presence of a scaling factor and a scale-free doubling/halving power law in both. This similarity suggests that simple integer ratios found between frequency domains might be interpreted as a form of *endogenous mode-locking*, similar to the harmonic relations found between stimulus and FFRs in the brain.

We propose that endogenous mode-locking could depict nested communication within biological systems. We extend this notion, suggesting that the specific configurations of peaks within HABBOs could act as indicators of various phenomenological states. Exploring harmonic

² The process by which a stable internal environment is maintained in a living organism, despite changes in external conditions.

³ A physiological mechanism of regulation where the human body anticipates and adjusts its energy use in response to environmental demands, thereby achieving stability through change.

structures in relation to physiological functions may lay the foundation for innovative adaptive musical structures, reflecting the intricate non-linear dynamics of brain activity and their association with the phenomenology of music. Current literature lacks comprehensive research investigating endogenous mode-locking and the harmonicity of ratios between nested brain oscillations, marking a significant area for future exploration.

5.2.2. General Resonance Theory of Consciousness

We position our discussion in alignment with the General Resonance Theory of Consciousness (GRTC), a recent panpsychist theory linking consciousness— or phenomenology— to Harmonic Brain-Body Oscillations (HABBOs). A key motivation of GRTC is the transformation of panpsychism from a purely philosophical stance to a testable scientific theory of consciousness. GRTC posits consciousness as a manifestation of resonance between coupled oscillators, inducing nested harmonic relationships within macro-structured conscious systems (Hunt et al., 2019). This resonance is a precursor to optimal information and energy flows, facilitating inter- and intra-system communication (Young et al., 2022). This theory delineates that the harmonic architectures within biological systems serve as a determinant of the associated phenomenology (Klimesch, 2018a), acting as a coherent mechanism for nested organization levels (F. Varela et al., 2001). For complex consciousnesses, such as that of humans, the unfolding of resonance in time is thought to operate at a level of (near-)criticality (O’Byrne & Jerbi, 2022b), where small alterations can catalyze drastic outcome variations. This indicates that local resonances are integral to initiating macro-state transitions (Hunt et al., 2019).

From this perspective, the brain mechanisms behind conscious processes can be regarded as a complex system that operates near a critical point of a phase transition. While displaying spontaneous activity and irregular dynamics in the disordered phase, an appropriate stimulus can transfer the brain to the ordered phase that exhibits long-range correlations and stable attractors. (Hunt et al., 2019)

From a GRTC perspective, the harmonic architecture of spontaneous activity embodies information about these transitions. Hence, local resonances can be defined as the increased likelihood of phase-coupling between proportionate spectral peaks and their sub- and inter-harmonics, potentially serving as predictors of emergent behavior. Our proposition encompasses the analysis of both temporal and spatial distributions of local resonances to anticipate macroscale phase transitions, reflecting trajectories and bifurcations in brain dynamics state space. A proposed mathematical heuristic for identifying spatial and temporal boundaries of conscious structures is by calculating the slowest shared resonance (Hunt, 2020; Young et al., 2022), which corresponds to the lower frequency through which subsystems communicate. We posit that this *slowest-common denominator* might correspond to shared subharmonics between subcomponents of a conscious system.

Our contributions, rooted in the Binary Hierarchy Brain-Body Oscillation Theory and GRTC, will be detailed in Section 7, emphasizing the development of tools to quantify emergent harmonic structures and derive multistable auditory percepts in brain signals. Prior to delving into our approach to bioharmonicity, a brief overview of conventional sonification techniques of electrophysiological signals is provided to elucidate our position and propose extensions in neurofeedback practices.

6. Sonification of Brain Signals: From Data to Auditory Patterns

Sonification is defined as the transformation of data relations into perceived relations in an acoustic signal, with the primary purpose of facilitating communication or interpretation (Kramer et al., 2010). It has sparked collaboration among musical composers and scientific researchers from various disciplines, frequently incorporating sophisticated technological tools into the process (Helmuth & Schedel, 2022). In the context of brain signals, sonification involves converting neural patterns into sounds that might offer insights into brain dynamics and functions.

This section delves into established sonification techniques, presents a novel approach termed 'harmonic audification,' and discusses its potential implications and applications.

6.1 Understanding Sonification

Sonification's challenge lies in balancing the inherent constraints of data with the versatility of sound (Grond & Hermann, 2012). The chosen sonification technique can largely be influenced by the nature of the data structure (Campo, 2007). Several methods have been employed over the years (Väljamäe et al., 2013):

1. **Audification:** A direct translation of EEG signals into audible content, resulting in soundscapes resembling pink noise due to the inverse relationship between frequency and power (Adrian & Matthews, 1934; Pritchard & Duke, 1992).
2. **Parameter Mapping:** This involves correlating a specific EEG feature with a sonification parameter (Campo, 2007).
3. **Model-Based Sonification:** EEG features are mapped to mathematical models, capturing more abstract neural dynamics (Halim et al., 2007).
4. **Generative Music:** This technique employs predefined musical rules and structures. For instance, (Miranda, 2006) designed a system where EEG power of different bands controlled generative musical rules. However, the harmonic structure of such systems remains constrained by preset rules.

6.2 Advancing with Harmonic Audification

While traditional sonification techniques offer valuable insights, there is a burgeoning interest in exploring the harmonic structures of brain signals (Klimesch, 2018a; Young et al., 2022). We propose 'harmonic audification' as a method that employs harmonic analysis of

biosignals to create adaptive musical structures. Unlike traditional methods that might focus on specific neurocognitive markers or direct translations, this technique aims to capture the interdependencies between multiple frequency domains, thereby reflecting their integrated functions.

The process of harmonic audification enables the creation of auditory perceptions derived from Harmonic Brain-Body Oscillations (HABBOs). It incorporates elements of pitch, rhythm, and timbre, coupled with adaptive tuning systems, to present a more detailed and nuanced portrayal of brain dynamics. Harmonic audification, with its emphasis on capturing the nuanced harmonies of brain dynamics, promises not just an auditory experience, but potentially a deeper understanding of the brain and its associated phenomenology. In the following section, we provide tools to compute measures of harmonicity and generate auditory patterns which can be fed back and matched to the bioharmonic structure from which they were derived.

7. Dynamical musical systems derived from neural dynamics

In this section, we will delve into the extraction of spectral peaks from electrophysiological signals, exploring methods that highlight the retrieval of their harmonic structure. Two distinct methods, Empirical Mode Decomposition (EMD) and Harmonic Recurrence, will be demonstrated to extract these spectral peaks. Following this, we will derive tuning systems which are fundamentally based on these spectral peaks and harmonic positions. Finally, we will examine two innovative methods to unfold the temporal aspects of brain harmonicity, focussing on generating spectral chords and considering consonance between successive spectral peaks.

7.1 Computation of spectral peaks in the framework of harmonic analysis

7.1.1. Empirical Mode Decomposition; a data driven approach to spectral decomposition.

Traditionally, the spectrum of M/EEG signals is categorized into five principal frequency bands: delta, theta, alpha, beta, and gamma, a division founded on cumulative empirical evidence (Cohen, 2017; Teplan, 2002). This method originated with the identification of the alpha peak as the inaugural predominant rhythm demarcating brain signals (Berger, 1929). Subsequently, diverse brain rhythms were labeled, corresponding to their discerned functional roles. A significant limitation of traditional frequency analysis methods in neuroscience is the treatment of frequency band boundaries as static, leading to somewhat arbitrary categorizations of brain rhythm frequencies. This inherent flaw is evident in instances where changes in the alpha peak, induced by altered states of consciousness, deviate substantially from the conventionally defined 8-12Hz range, particularly in extreme cases (Mierau et al., 2017).

Empirical Mode Decomposition (EMD) emerges as a pivotal, data-driven alternative, facilitating the decomposition of a signal into intrinsic mode functions (IMF) using a sifting procedure (Rilling et al., 2003a). Functioning as a dyadic filter bank, EMD iteratively isolates higher frequency data, aligning the resultant IMFs in a \log_2 relationship. In line with (Klimesch, 2018a), our proposition hinges on the octave-based configuration of the brain's biological oscillation, implying that the examination of IMFs could unveil nuanced insights into biorhythms and their intrinsic spectral hierarchy.

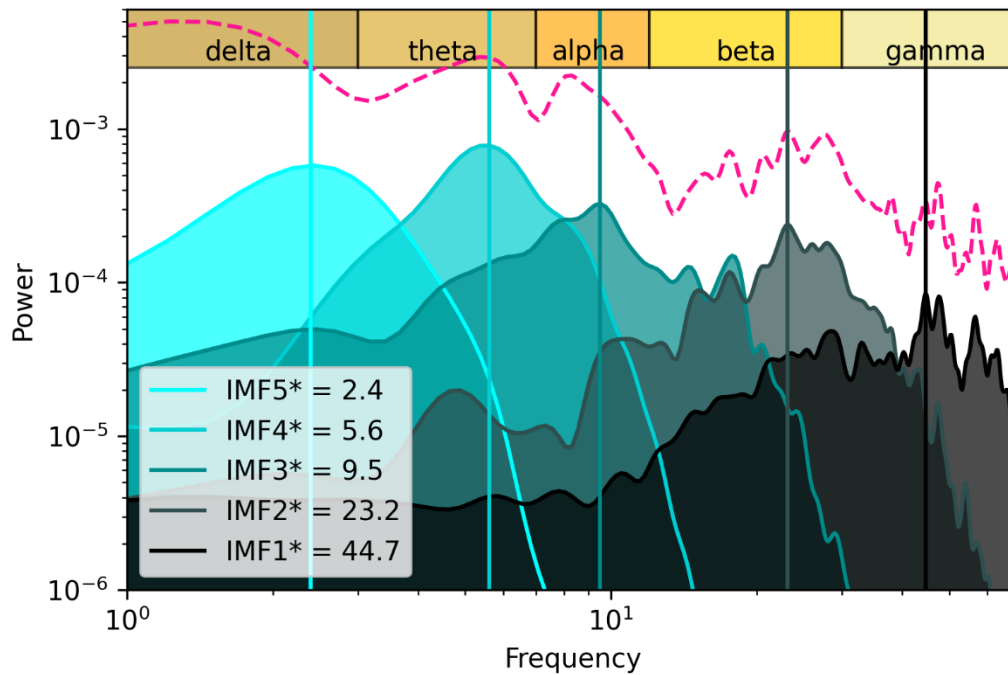


Figure 4.1. Peaks extraction based on Empirical Mode Decomposition (EMD). Power Spectrum Density plot of five Intrinsic Mode Functions (IMF; blue) and global signal (pink). The bin with maximum power is selected as a peak and compared to classical frequency bands: Delta (1-3Hz), Theta (3-7Hz), Alpha (7-12Hz), Beta (12-30Hz), Gamma (30-60Hz). Stars (*) beside IMFs in the legend mean that the peak falls within classical frequency band.

Additionally, EMD has been recently applied to MEG data for analyzing frequency bands, demonstrating superior precision over conventional time-frequency analyses (Skiteva et al., 2016). Consequently, a data-driven strategy for identifying spectral peaks in brain signals involves initial computation of EMD, followed by considering each IMF as indicative of the activity within a specific frequency band. **Figure 4.1.** illustrates the power spectral density (PSD) plot of each IMF, juxtaposed with the PSD of the raw signal depicted in pink. A peak is determined from each IMF by conducting the Welch Transform and identifying the frequency bin with the utmost power. Notably, these peaks align with classical frequency bands, despite being derived from an approach that is agnostic to the predefined ranges of these bands. This might be attributed to the

fact that classical bands are structured in a \log_2 fashion, with each band being approximately one octave above the previous. EMD's octave-based sifting process inherently captures this spectral arrangement. Consequently, EMD presents an appropriate method for the investigation of HABBOs. A detailed exploration of such comparisons exceeds the scope of this chapter and would require further inquiries.

7.1.2. Harmonic recurrence in M/EEG spectral architecture

We suggest a second approach for selecting spectral peaks that reflects the inherent harmonic structure of the signal, which we term *harmonic recurrence*. This approach computes the Welch transform to extract all peaks and amplitudes of the spectrum. Afterwards, the harmonic series of each peak is compared to all other peaks to identify those that have the highest recurrence in the spectrum. Hence, selected peaks are the ones that have a maximum number of harmonics that match other peaks in the spectrum, reflecting their embeddedness across multiple spectral scales. Using this method, we can also quantify the *inter-harmonic concordance*, which corresponds to the alignment of harmonics of two different peaks (e.g., harmonics 11-yellow and 18-blue in **Figure 4.2.**). Spectral peaks can therefore be identified solely based on their harmonic recurrence, or by selecting peaks that also share inter-harmonic concordance. This method is analogous to the Harmonic Product Spectrum, a method traditionally used for voice pitch tracking, which downsamples iteratively the original signal by a factor of two and looks for recurrent spectral peaks across the multiple downsampled versions of the signal (Sripriya & Nagarajan, 2013).

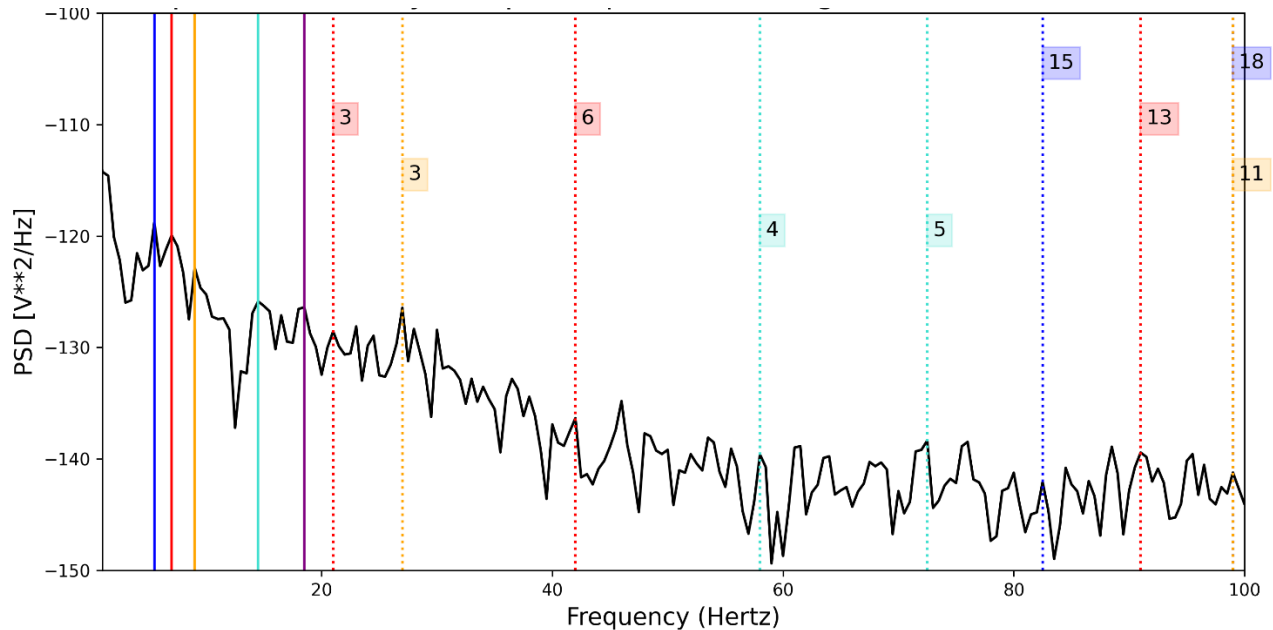


Figure 4.2. Peaks selection using harmonic recurrence method. Welch transform has been computed on a single time series to derive the Power Spectrum Density. Then, peaks are identified using scipy *find_peaks*. A pairwise comparison is done to determine if a peak is a harmonic of another. Selected peaks (solid lines) are peaks having the highest number of harmonics (dashed lines) as other peaks of the spectrum. Numbers on dashed lines correspond to the harmonic positions. Hence, the blue peak has its 15th and 18th harmonic as other peaks, the yellow peak has its 3rd and 11th harmonic as other peaks, while the 11th harmonic of the yellow peak and the 18th harmonic of the blue peak coincide.

7.2. Neural tunings as embedding of brain harmonic structures

We considered M/EEG spectral peaks and their associated frequency ratios as expressing both functionally and musically relevant information that can be used to derive tuning systems. We applied two methods to derive tunings exploiting spectral peaks and amplitudes (dissonance curves), as well as the position of recurrent harmonics (harmonic tunings).

7.2.1. Dissonance curves

Grounded in Sethares' demonstration of the isomorphism between timbre and tuning (Sethares, 2005b), we derived dissonance curves from the values of the spectral peaks and their related amplitude. Each interval is assigned a dissonance value, determined by assessing the harmonicity between every pair of peaks and amplitudes. Hence, the dissonance curve expresses

the dissonance for a range of frequency ratios by scaling the frequencies and recalculating dissonance over a defined grid. This generates a curve that visually represents how dissonance changes with different intervals, allowing for the evaluation of musical consonance and dissonance over the span of one or multiple octaves. A tuning, represented by a set of frequency ratios, is then established by observing the local minima of the dissonance curve. Illustrated in **Figure 4.3**, are the dissonance curves derived from spectral peaks of a series of MEG sensors located in the occipital regions, juxtaposed with the local minima of the 12-steps equal temperament (12-TET; highlighted by red dashed lines). Intriguingly, multiple sensors share some local minima (e.g., $9/7$ is common across three sensors), indicating a convergence in their harmonic structure. These dissonance curves are indicative of tunings that mirror the timbral structure inherent in the electrophysiological signal and can be used as creative tools for musical exploration.

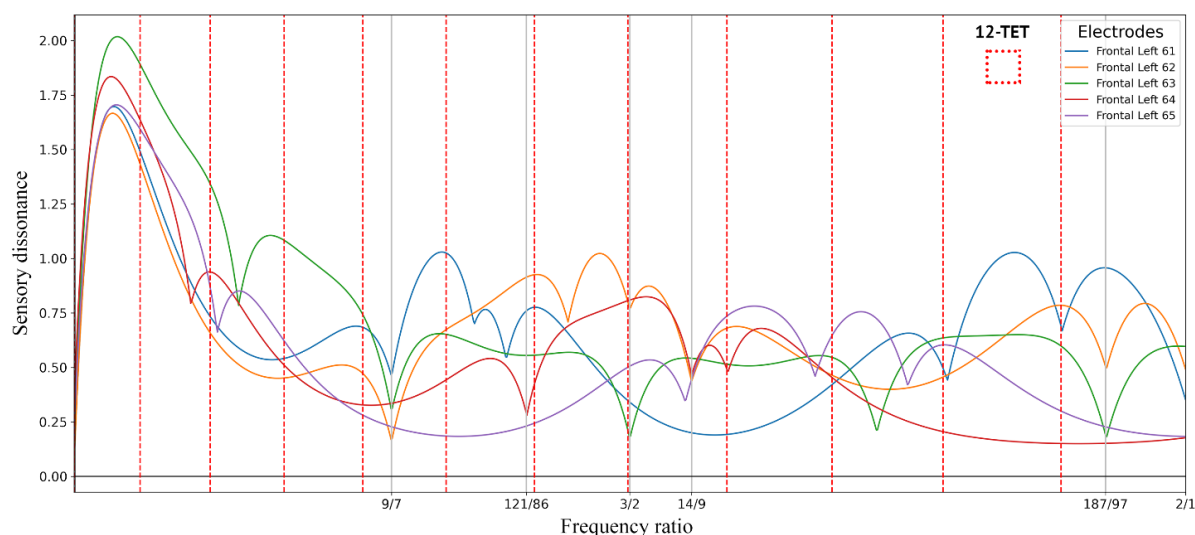


Figure 4.3. Dissonance curves from multiple MEG sensors. Each colored line corresponds to the dissonance curve of one electrode based on spectral peaks derived using EMD. Grey and red vertical lines represent the dissonance local minima shared between at least two MEG dissonance curves and of 12-TET equal temperament, respectively.

7.2.2. Harmonic tunings

An alternative methodology for generating neural tunings involves employing the positions of harmonics identified via the harmonic recurrence method, akin to the strategy employed in constructing the 8th Octave Overtone Tuning (Reinhard, 2011). Consequently, each position within the harmonic set is iteratively divided by 2 until a ratio lying between the unison (1:1) and the octave (2:1) is obtained. This iterative process can be mathematically represented as follows:

$$R_i = \frac{H_i}{2^n} \quad (1)$$

In *formula 1*, R_i denotes the resulting ratio for the i -th harmonic, H_i represents the original position of the i -th harmonic, and n is the number of times the harmonic position is divided by 2 to fall within the unison to octave range.

Both strategies for constructing tunings offer dynamic avenues for music creators, allowing exploration of novel musical systems that draw inspiration from their own real-time biological processes. Corresponding audio examples and .tun files for both tuning variants are made accessible via a provided an open source *osf* repository:

https://osf.io/fx7er/?view_only=211b000c6482471facd3d8dcc6c93580.

7.3. Transitional harmony in brain oscillations

7.3.1. Deriving spectral chords from instantaneous frequencies using Hilbert-Huang transform

Previous sections detailed the derivation of (static) tuning systems from single time series, utilizing pairs of spectral peaks and amplitude (representing timbral information) to construct dissonance curves and employing series of harmonic positions to generate harmonic tunings. In

this section, a method is introduced to generate a set of spectral chords from consecutive moments of harmonicity within a singular time series (refer to **Fig. 4.4A**). As a first step, the Hilbert transform is performed on a set of intrinsic mode functions (IMFs), allowing for the extraction of instantaneous frequency (IF) information. Subsequently, harmonicity (e.g. harmonic similarity) is computed among all pairs of IF and for each timepoint. A spectral chord is identified when the harmonicity reaches a predefined threshold. This technique facilitates the extraction of sequential chords, mirroring the temporal evolution of brain dynamics within a singular time series. This offers valuable insights into the nested spectral structure of the signal and can be applied within the framework of dynamic musical systems.

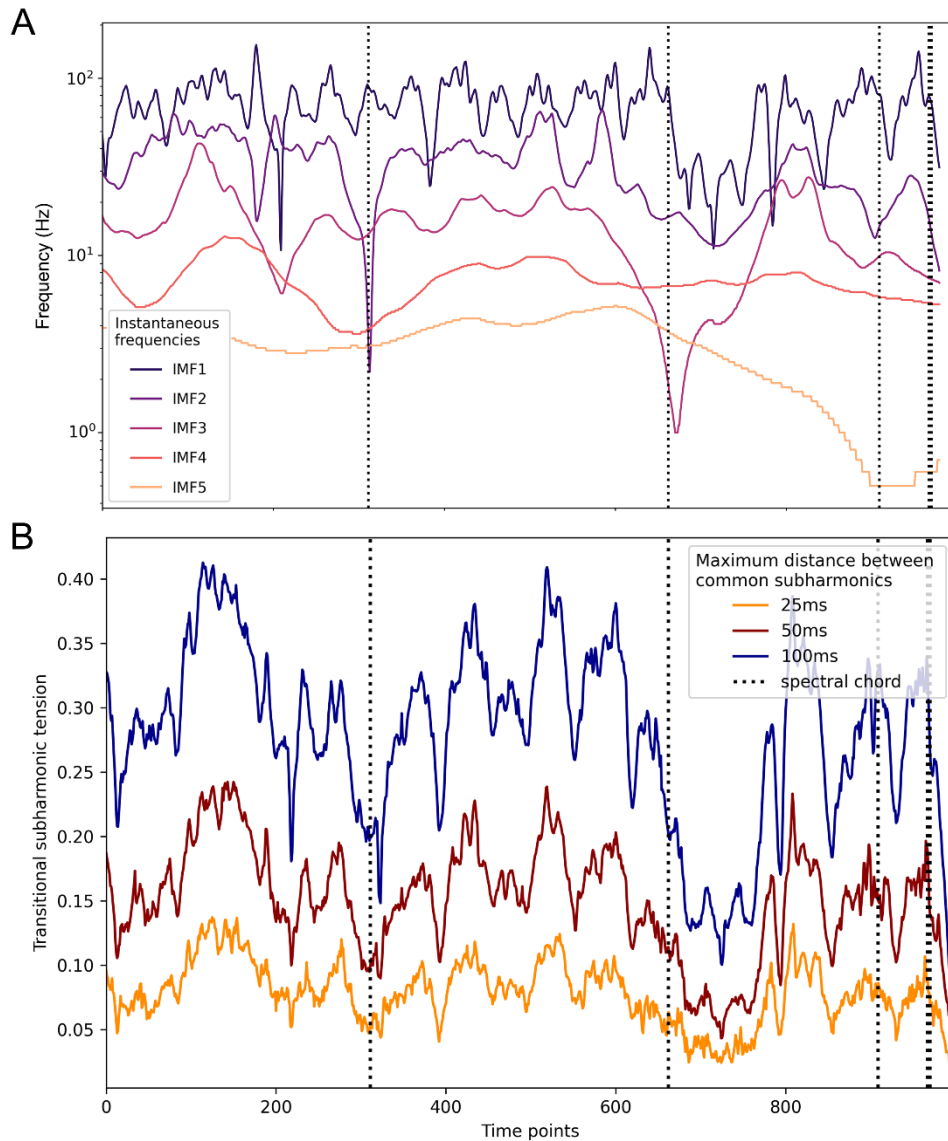


Figure 4.4. Transitional (sub)harmony using instantaneous frequencies of intrinsic mode functions (Hilbert-Huang Transform). (A) Spectral chords based on harmonic similarity threshold. For every point in time, harmonic similarity was computed on each pair of instantaneous frequencies among the five IMFs. When the average harmonic similarity exceeded a value of 20, a spectral chord was identified, corresponding to dashed gray lines. **(B) Transitional subharmonic tension.** The transitional subharmonic tension represents the level of subharmonic congruence between two successive sets of frequencies. Each set of frequencies corresponds to instantaneous frequencies (IFs) of intrinsic mode functions (IMFs) at a specific moment in time. Congruent subharmonics are identified with maximum distance thresholds set to 25ms (yellow), 50ms (red), and 100ms (blue). Dotted black lines are moments of high harmonic similarity between the peaks of a single set of frequencies (stationary harmony).

7.3.2. Subharmonic tension and resolution in brain dynamics

The focus of this section is to adapt the concept of transitional harmony (Chan et al., 2019a) to explore the microtonal structures of brain signals, through analyzing the relationship between successive sets of spectral peaks, derived from the instantaneous frequencies (IFs) of IMFs.

Subharmonic tension is a metric that quantifies the degree of dissonance or stability within a group of frequencies, reflecting the degree of temporal irregularity among subharmonics of different frequency peaks. Initially, the process involves calculating the first n subharmonics for each frequency to identify those that are common within a specified temporal threshold. The measure of subharmonic tension (ST) is then determined by averaging the normalized temporal discrepancies of these common subharmonics. The temporal discrepancy for each common subharmonic pair is represented by the absolute temporal distance (Δt), which is divided by the subharmonic frequency value (Sub_i), ensuring the ratio is dimensionally consistent. Finally, the subharmonic tension is obtained by summing these normalized values across all identified common subharmonic pairs and dividing by the total count of such pairs (N), yielding a single metric that captures the average 'tension' due to temporal irregularities between subharmonics within an octave span.

$$\text{Subharmonic Tension (ST)} = \frac{1}{N} \sum_{i=1}^N \left(\frac{\Delta t_i}{Sub_i} \right) \quad (2)$$

The application of this methodology allows for the visualization of fluctuations in tension-resolution patterns in brain dynamics (refer to **Fig. 4.4B**). Intriguingly, periods of high stationary

harmonicity (identified earlier in Section 7.3.1) seem to spark transitions in patterns of tension and resolution, offering hints into the interconnectedness between stationary and transitional harmony.

8. Creative brain-computer interfaces

In this section, we present different avenues for the integration of bioharmonicity in artistic and scientific endeavors. In line with principles of Naturalization of Phenomenology (Roy et al., 1999), we design *creative brain-computer interfaces* (cBCIs) to procedurally (re)generate “[...] processes involving a phenomenalization of physical objectivity” (Roy et al., 1999). In that sense, our approach to cBCIs is an explicit implementation of a fluid circulation between first-person (phenomenology) and third person (brain signals) perspectives (i.e. generative passages) transcending the stationary description of isomorphisms. In doing so, we intend to propose a framework in which both the realm of lived experience and our ability to investigate its complex biological underpinnings could be expanded.

We have already seen that computational models of consonance as well as dynamical systems modeling tools have allowed musicians to develop instruments expressing oscillatory features that represent self-organizing behaviors at multiple scales. Here, we built on the intuitive notion that harmonicity reveals important information of any self-organizing system. Accordingly, we presented tools allowing us to appropriately analyze the (harmonic) relationships between frequency-domain properties of brain signals.

We define our cBCI as a system interfacing metastable (harmonic) properties of brain activity into sensory feedback loops to induce altered perceptual experiences. In simple terms, we expect the computer to “resonate” with the user by matching the harmonic architecture of both biological processes and sensory feedback. In providing feedback that is both phenomenologically and physically reflecting endogenous states, cBCIs are intended to foster the impression of “creating” aesthetic artifacts through acts of perception, thereby dissolving the

frontier between subject and object. Feedbacking biological processes that are musical in terms of their harmonic content will perhaps lead to emergent forms of expression. It might also facilitate the exploration of new trajectories of states of consciousness through immersive neurofeedback experiences.

We discuss novel musical performance tools in section 8.1, along with possible applications for non-musicians. In 8.2, we lay down a blueprint for testing GRTC's hypotheses by suggesting ways to operationalize resonance through bioharmonic measurements. Subsequently, we discuss the possibility of developing Bayesian modeling approaches as potential machine learning frameworks accounting for multiscale temporal dynamics of HABBOS. We discuss how such models provide interpretable human-computer interactions allowing the investigation of emergent properties of brain dynamics related to phenomenology.

8.1. Integrating harmonic audification in biofeedback systems

This section explores the integration of harmonic audification in Brain-Computer Interfaces (cBCIs), emphasizing its application in both passive and active biofeedback systems. Our approach utilizes HABBOS to offer users immersive musical experiences. The design of these interfaces faces two main challenges: creating coherent tension-resolution patterns and aligning them with the user's lived experience. We propose that brain-body oscillations offer natural tension-resolution patterns that could be used within cBCIs to promote a feeling of connection with the interface.

Passive cBCIs (Zander & Kothe, 2011) include generative music systems based on spectral chords and adaptive tunings, as detailed in Sections 7.2 and 7.3. These elements reflect and adapt to the user's HABBOS, allowing for a personalized auditory exploration. For example, spectral chords can be computed in real time and fed back to the user as immersive auditory soundscapes. Beyond biofeedback, harmonic audification can also inspire music creators,

particularly in improvisation and microtonal compositions. Active cBCIs (Zander & Kothe, 2011) could, for instance, map adaptive tunings to MIDI controllers, offering improvisers novel musical possibilities tied to their internal states. This mapping adapts in real-time to changes in brain parameters, as demonstrated in our accompanying audio files.

In sum, applications of harmonic audification may foster, similarly to contemplative practices (Dorjee, 2016), “metacognitive self-regulatory processes” by allowing the user to weigh how their states of consciousness are instantiated in sound. In line with neurophenomenology, such interfaces promote “mindful, open-ended analyses of experience” (F. J. Varela et al., 1991, p. 81), by shedding light on its “momentariness” (p.73). In fact, cBCIs could bring about cross-fertilization between neuroscience and contemplative/mindfulness practices through the phenomenalization of emergent biological processes. Such profound human experiences guided by formal or informal contemplative practices might even be deepened by immersive audiovisual spaces as well as augmented/virtual reality devices.

8.2. Creative brain-computer interfaces as generative passages

8.2.1. Experimental BCI protocols testing the General Resonance Theory

The GRTC posits that consciousness emerges from the synchronization of systems that resonate together. We have shown how harmonicity can be computed on brain signals and hypothesize that consonance between spectral peaks could constitute a marker of resonance, since oscillators that synchronize in frequency will tend to naturally synchronize in phase, based on Kuramoto model (Acebrón et al., 2005). Moreover, measures of phase synchronization, such as bicoherence and phase-lag index, could directly test whether consonant spectral peaks tend to synchronize in phase and therefore enter in resonance.

In the case of neurofeedback applications, we can extend the framework of GRTC to human-machine interactions. Coherently, we speculate that a cBCI matching the harmonic

architectures of brain signal and sensory feedback would facilitate the emergence of resonance between the human and the machine, and therefore of a distributed dynamical system. This mechanism of *harmonic matching* might be key for the user to reify the content provided by the neurofeedback system. Such distributed dynamics between human and machine forms a generative passage allowing to bridge the gap between first- and third-person perspectives.

We suggest that the sense of agency could be fostered through the matching of sensory feedback properties with the HABBOS of the user (Berkovich-Ohana & Glicksohn, 2014). By doing so, human-machine resonance might enable a process of perceptual identification with the content of the sensory feedback. This resonance might in turn be measured by combining (sub)harmonicity and phase coupling metrics since resonance requires harmonious ratios between frequency peaks, as well as their phase(mode)-locking. We suggest that the comparison of real vs. sham neurofeedback, in the context of harmonic audification, could provide a way to test hypotheses related with the GRTC, such as how human-machine resonance could elicit a feeling of agency.

8.2.2. A Bayesian account of transitional harmony in the context of neurofeedback

This section explores the application of a Bayesian machine learning framework to model the transitional harmony of brain-body oscillations (BBOs) within neurofeedback systems. Bayesian models have been instrumental in the analysis of musical attributes such as pitch, dynamics, and timbre in audio signals (Davy & Godsill, 2003; Duan et al., 2008; Yoshii & Goto, 2012), and have extended to the domain of musical key determination (Temperley, 2004), pitch class detection (Rhodes et al., 2009), identification of time-varying harmonic components (Duan et al., 2008; Dubois & Davy, 2007), and the elucidation of harmonic structures in jazz (Harasim, 2020). This collective research underscores the Bayesian framework's efficacy in unraveling the complexity of music and its phenomenological correlations.

A Bayesian framework is particularly advantageous in dynamically describing musical tension, ambiguity, and expectation (Temperley, 2004). Uncertainty, a central element of both music and phenomenological experiences, manifests in music as a web of potential harmonic trajectories over time, each with its tension-resolution pattern. When modeled computationally, these trajectories offer a rich landscape for exploration. It is an open question whether perception is confined to a singular trajectory or is capable of navigating multiple paths concurrently. Attentional focus may play a pivotal role in this perceptual process, with specific trajectories becoming prominent and uncertainty diminishing as harmonic progressions resolve. Thus, employing a Bayesian approach to model transitional harmony and its associated uncertainties could be instrumental in addressing the intricacies of harmonic structures embedded within both music and brain signals.

In the case of phenomenology, uncertainty and *surprise* orientate attention through the prioritization of unpredictable sensory information for learning better representations of the world. This perspective aligns with the predictive coding framework, which posits that perception is an active process aimed at minimizing the discrepancy between expected and received sensory input (Friston, 2005). This framework is in harmony with a Bayesian approach to brain function, suggesting that the brain interprets sensory data probabilistically, effectively treating perceptions as statistical inferences (Knill & Pouget, 2004; Mathys et al., 2011). Within the context of closed-loop brain-computer interfaces (cBCIs), a Bayesian model could significantly advance our grasp of the interplay between phenomenological experiences and their neural underpinnings by integrating both subjective and objective data through continuous feedback (Bagdasaryan & Quyen, 2013).

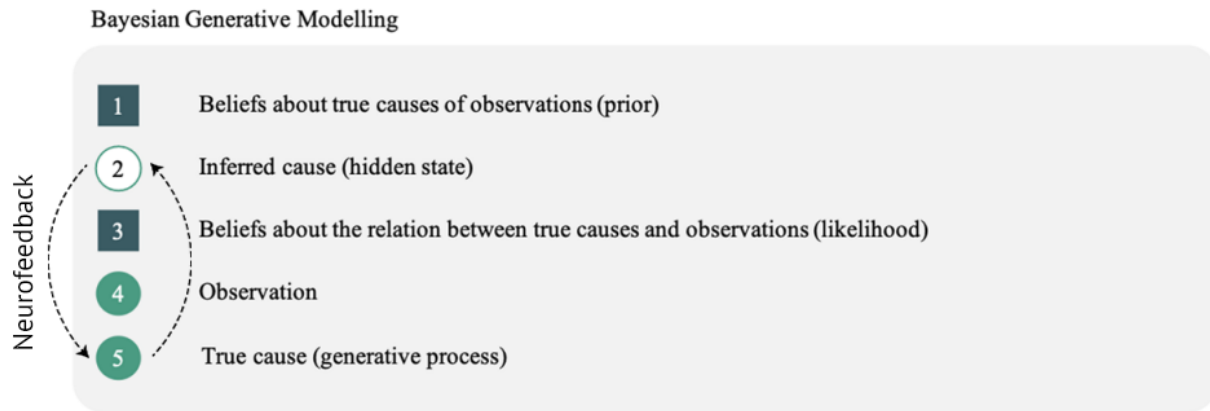


Figure 4.5. A computational neurophenomenological account of neurofeedback. From Ramstead et al., (2022)

A Bayesian model issued from computational (neuro)phenomenology (Ramstead et al., 2022) provided insights regarding how machines (cBCIs applications) could more fully participate in the user’s resonance with the musical system (see **Figure 4.5.**, adapted from (Ramstead et al., 2022)). A generative model that learns how acoustics temporally relate to HABBOs would essentially gain representations of states of consciousness (arrow from 5 to 2), and therefore generate them in the form of (harmonic) audification. We presume that in projecting the hidden state of subjective experience onto the true cause of experience (arrow from 2 to 5), beliefs about true cause of experience (priors) become in circularity with the true cause of experience, potentially giving rise to altered states of consciousness.

9. Conclusion

This chapter has explored the intersection of computational harmonicity and brain dynamics, suggesting a novel paradigm for biologically-informed adaptive music. We have discussed the Binary Hierarchy Brain-Body Oscillation theory (Klimesch, 2018a) and the General Resonance Theory of Consciousness (GRTC) (Hunt et al., 2019), which both posit that harmonic

patterns within biosignals are reflective of underlying neurophysiological processes and states of consciousness. We have introduced computational methods for extracting biotunings and delineating both stationary and transitional harmonic structures associated with brain activity. Integrating these methods with closed-loop brain-computer interfaces (cBCI), we proposed a Bayesian framework to effectively model the dynamics of transitional harmony within sensory feedback systems.

To facilitate the practical investigation of these concepts, the Biotuner toolbox (Bellemare-Pepin, *in prep*) emerges as a significant resource. It enables hands-on exploration and application of these theoretical ideas, providing a tangible means for researchers and practitioners to engage with and advance the understanding of these complex harmonic processes in brain dynamics.

Our goal is to augment traditional computational strategies for analyzing brain signals with harmonic analysis techniques, contributing to the advancement of neurophenomenology and the initiative to Naturalize Phenomenology (Roy et al., 1999). We view this work as a first step towards empirical cross-fertilization between music theory and neuroscience, aspiring to unlock new insights into cross-frequency coupling and resonance phenomena and their connection to phenomenological experiences. Through this lens, we imagine brain dynamics as an orchestral jam session, with self-organizing neural oscillators performing in a (near) critical state, creating tension and resolution patterns over various spatiotemporal scales, thereby orchestrating adaptive behavior.

Biotuner: A Modality-Agnostic Python Toolbox for the Harmonic Analysis of Time Series

Abstract

The Biotuner Toolbox is an innovative python toolbox that analyzes biosignals by blending principles from neuroscience, music theory, and signal processing. It introduces a new approach to understanding brain oscillations by applying musical concepts like harmony, rhythm, and scale construction. The central component, the *biotuner_object*, processes a wide range of signal types, from neural data to environmental sounds. Other main objects in the toolbox expand its functionality through the parameters of time (time-resolved harmonicity), space (harmonic connectivity) and spectrum (harmonic spectrum). This toolbox enhances our scientific understanding of biosignals and crosses into the realm of artistic expression, allowing for creative interpretations of complex natural patterns. It stands as a versatile tool for both researchers and artists, encouraging exploration and discovery across disciplinary boundaries.

Introduction

Oscillations from brain's electromagnetic signals are integral to various cognitive processes (Samaha et al., 2020), as well as perceptual processes, such as the processing of auditory stimuli (Baltus & Herrmann, 2016; Gourévitch et al., 2020; Henao et al., 2020). These oscillations represent a complex interplay of frequencies, where harmonicity emerges as a key organizing principle (Klimesch, 2013b, 2018b; Young et al., 2022). Understanding this harmonic structure can yield profound insights into the brain functionality, revealing a unique perspective on the neural correlates of cognitive processes. (Carlqvist et al., 2005; Isler et al., 2008; Palva et al., 2005). I propose that music theory offers a valuable framework for applying its principles to the processing of biosignals. Models of harmony and rhythm can be useful for both artistic creation and for uncovering significant features in biosignals, enhancing their scientific study and interpretation (Bogdanov et al., 2013; McFee et al., 2015). They offer novel methods to interpret the intricate patterns and structures within biosignals. For instance, the concept of consonance and dissonance⁴ in music can be translated into understanding the harmonic relationships in brain oscillations, offering a new perspective on their functional significance.

The Biotuner Toolbox emerges at this crossroads of neuroscience and music theory. It is an innovative python toolbox designed to harness the principles of music theory for the analysis of biosignals. The underlying philosophy of the Biotuner is that the theory of musical harmony provides a distinctive lens through which to view tension-resolution patterns in any dynamical system. For neuroscientists, Biotuner offers a gateway to explore novel methodologies in signal processing, opening up new avenues for research in brain dynamics and cognitive neuroscience. It allows for the extraction of harmonic components, the computation of rhythmic structures, and

⁴ Consonance, or harmonicity, refers to the pleasantness of a musical interval, often measured through the simplicity of integer ratios. Dissonance corresponds to the opposite concept.

the application of harmonicity metrics to biosignals, thereby enabling a deeper insight into their harmonic nature. Conversely, for artists and musicians, Biotuner serves as a tool for inspiration and creative exploration, enabling intuitive perceptions of natural phenomena. By translating biological rhythms and patterns into musical elements, it provides a unique source for composition and sound art. Beyond a technical resource, Biotuner is a platform for exploration and discovery. This symbiotic relationship between science and art fosters creativity and enriches our understanding of both fields.

This paper is structured into three main sections, the first two mirroring the inherent organization of the Biotuner Toolbox. First, the Biotuner Object is presented, designed to examine the harmonic structure of time series data, extracting musically relevant details like tunings⁵, rhythms, and levels of consonance. The second section introduces three higher-level objects designed to compute transitional harmony over time, assess harmonic connectivity between different signals, and analyze the harmonic spectrum. Finally, I present practical applications, from the sonification of various natural phenomena to methodologies in cognitive neuroscience.

Biotuner Object

At the heart of the Biotuner is the *biotuner_object*, which interfaces with various modules for comprehensive harmonic signal analysis (refer to **Fig. 5.1**). It orchestrates the execution of methods for peak extraction, peak extension, metrics computation, time-resolved harmonicity, tuning construction, and rhythm construction, thereby serving as a central hub for the toolbox's functionality. This object is specifically engineered to process single time series data and is versatile enough for applications in various fields, such as electrophysiology (including ECG,

⁵ A tuning is a set of intervals traditionally spanning from the unison (1:1) to the octave (2:1), used to establish pitch relationships between notes in music

EEG, PPG, organoid, and plants), audio data analysis, seismography, and the study of gravitational waves.

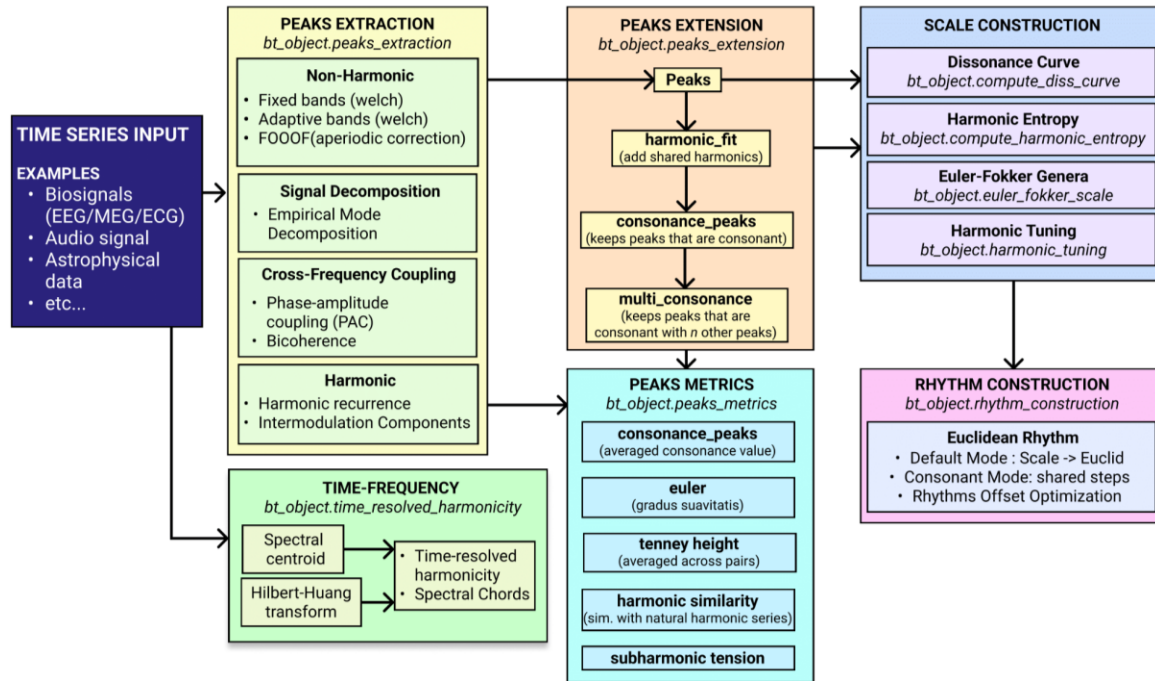


Figure 5.1. Architecture of the Biotuner Object. The Biotuner Object can process a diverse range of input types. Invoking the *peaks_extraction* method enables subsequent calls to the *peaks_extension*, *peaks_metrics*, and family of *scale_construction* methods. The *time_resolved_harmonicity* method can be directly executed, producing a time series of harmonicity values along with spectral chords, which correspond to moments of heightened consonance.

Peaks Extraction Method

Brain signals, such as those measured by electroencephalography (EEG), are complex representations of neural activity. These signals are composed of various oscillations, each with its own frequency, amplitude, and phase. Peaks in these signals represent points of maximum amplitude in a particular frequency band and are indicative of concentrated neural activity. Understanding these peaks is crucial as their relative proportions often correlate with specific cognitive and perceptual processes. For instance, the frequency ratios between brain spectral peaks typically exhibit a doubling progression during alert wakefulness, with each step increasing

by a factor of two raised to the power of some integer, whereas these frequency ratios become irrational during sleep (Rassi et al., 2019). By analyzing the patterns and distributions of these peaks, we can not only gain insights into how their organization is associated with specific cognitive states, but also derive bio-inspired harmonic structures that could be used for musical composition. The Biotuner implements a variety of peak extraction approaches, each tailored to identify significant frequency components from complex time-series data. The present section is structured to first introduce traditional non-harmonic peak extraction methods, followed by signal decomposition and cross-frequency coupling-based techniques borrowed from neuroscience. Finally, it explores peak selection based on harmonic properties, drawing inspiration from music theory. This illustrates the diverse approaches for analyzing brain signals and their rationale for both cognitive science and musical composition.

Non-Harmonic Peak Extractions

The three non-harmonic methods are based on the principles of Power Spectrum Density (PSD) computation, utilizing the Welch method for this purpose (Zhao & He, 2013).

Fixed: A set of fixed frequency bands is determined. Peaks are identified as frequency bins exhibiting the highest power within each band. This technique is useful when interested in frequency peaks that fall within the classical bands of analysis, such as the alpha band in EEG signals.

Adapt: This method derives frequency bands based on the position of the alpha peak. The alpha peak is first detected, then other bands are derived from the alpha band, according to Klimesch's algorithm (Klimesch, 2013b). This method allows for a more responsive analysis that adjusts to the signal's dominant rhythm.

FOOOF: FOOOF (Fitting Oscillations & One Over F) is applied on PSD to delineate the aperiodic component from the underlying physiological spectral peaks (Donoghue et al., 2020). Previous

studies have established that biological signals consist of both oscillations and an aperiodic trend. The process of identifying physiologically meaningful oscillatory power benefits from the removal of this aperiodic trend (Del Bianco et al., 2023). Therefore, spectral peaks are identified after removing the aperiodic component of the signal.

Signal Decomposition Based Peak Extraction

Empirical Mode Decomposition (EMD): EMD is an advanced signal processing technique that breaks down complex signals into simpler components known as Intrinsic Mode Functions (IMFs). Each IMF represents a different frequency component of the original signal, with the frequencies typically arranged on a logarithmic scale, which means each subsequent frequency band is proportionally wider than the previous one (Quinn et al., 2021; Rilling et al., 2003b). The PSD provides a measure of the power present within frequency bands, and the peaks in the PSD highlight the most dominant frequencies, or the 'loudest' parts of the signal within those bands. EMD offers the advantage of being data-driven, enabling the identification of frequency bands without imposing predefined assumptions, such as those pertaining to classical canonical spectral bands in EEG (e.g., delta, theta, alpha, beta, and gamma). This provides a more transparent method for extracting spectral peaks from complex signals.

Cross-Frequency Coupling-Based Peak Extraction

Bicoherence: Bicoherence is a normalized form of the bispectrum⁶, used in signal processing. It quantifies the degree of phase coupling between different frequency components of a signal. Mathematically, it measures the correlation between the phase of a signal at one frequency with the phase of a signal at another frequency, normalized to a value between 0 and 1. Measures the

⁶ Frequency-domain analysis tool that extends the concept of the power spectrum to higher-order spectra. It measures the phase relationship between different frequency components of a signal and is used to identify nonlinear interactions and phase coupling within the signal.

normalized cross-bispectrum, a third-order moment in the frequency domain. This method assesses phase-phase coupling⁷, offering insights into the complex interactions between different frequency components of the signal. The peaks correspond to the pairs of frequencies exhibiting the highest bicoherence in the comodulogram⁸. Bicoherence is particularly useful in identifying nonlinear interactions and coherence in systems where multiple frequency components interact, such as in neurophysiological signal analysis (Shahbazi Avarvand et al., 2018) or in the study of turbulent fluid dynamics (Itoh et al., 2005).

Phase-Amplitude Coupling (PAC): Measures the coupling between the phase of low-frequency components and the amplitude of high-frequency components. The peaks correspond to the pairs of frequencies exhibiting the highest PAC in the comodulogram. This method proves useful in understanding the mechanisms of neural communication and synchronization, particularly in cognitive and neurological processes, where such coupling is believed to play a crucial role in information processing and neural network dynamics (Cohen et al., 2009; Giehl et al., 2021b; Iquebal et al., 2020; Wei et al., 2007). In a musical context, frequency pairs identified through both bicoherence and PAC methods can be interpreted as dyads, mirroring the coupling of biosignal peak frequencies in musical notes.

Peak Selection Based on Harmonic Properties

The two following methods are designed to look at the structure of spectral peaks to determine which ones are going to be selected, based on either the presence of intermodulation components, or of harmonic recurrence. Therefore, these methods specifically focus on the

⁷ Phase-phase coupling refers to the synchronization or statistical correlation of the phase angles between two oscillatory signals, indicating temporal alignment or interdependence of their cycles.

⁸ A comodulogram is a matrix representation that illustrates the strength of cross-frequency coupling between different frequency components of a signal.

harmonic structure of the signal to identify spectral peaks. They both rely on the Welch method to estimate PSD and extract all spectral peaks.

Endogenous InterModulation Components (EIMC): Intermodulation components (IMCs) are frequencies that emerge from the nonlinear mixing of two or more frequencies, often observed as the sum or difference of the original frequencies or their harmonics (e.g., f_1+f_2 , f_1+2f_2 , f_1-f_2 , f_1-2f_2) (Gordon et al., 2019). In music, these components are called sidebands, and result from different audio synthesis processes (Farnell, 2010; Puckette, 2007). This method computes the IMCs for each pair of peaks and compares them with all other peak values. Pairs of peaks with the highest number of IMCs as other peaks are identified.

Harmonic Recurrence: This method identifies spectral peaks that have the highest recurrence in the spectrum based on their harmonic series⁹. Peaks with the highest number of harmonics as other peaks are identified. It underscores the significance of recurrent harmonic structures within the signal.

The performances of various methods, excluding cross-frequency coupling methods and the Adapt method, are depicted in **Figure 5.2**. This figure demonstrates that all the methods effectively identify spectral peaks in both harmonic and brain-simulated signals. The performance of these methods remains comparable until a noise level of approximately 15-20 dB is reached. At this point, the EMD method shows a slight decrease in performance, and FOOOF ceases to identify peaks, indicating the absence of *physiologically relevant* peaks. Beyond 25 dB, the performance of all methods levels out and becomes comparable once again. Similar patterns are observed for both simple combined oscillations and simulated EEG signals, suggesting that these

⁹ Sequence of frequencies that are integer multiples of a fundamental frequency

methods are well-suited for extracting oscillatory peaks in biosignals. This analysis confirms the reliability of these methods in accurately retrieving frequency peaks from complex signals.

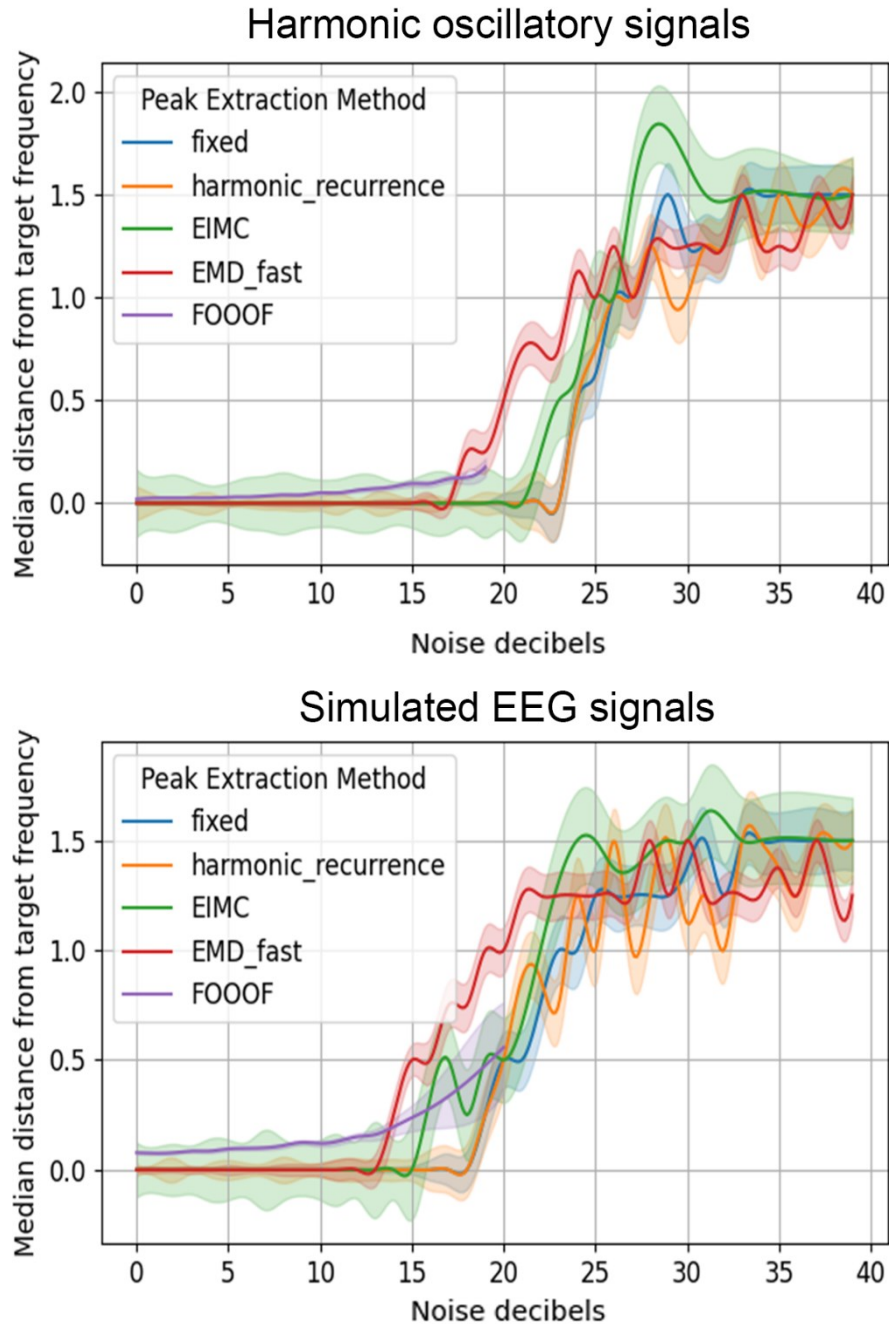


Figure 5.2. Performance analysis of different peak extraction methods applied to harmonic oscillatory signals (top) simulated brain signals (bottom), across increasing levels of noise decibels. The median distance reflects the extraction accuracy, with lower values indicating higher precision. The shadowed areas indicate the 95% confidence interval for the median distance across 100 bootstrap iterations. Harmonic signals were generated by combining sinusoidal frequencies at 2, 6, 12, and 24Hz, while simulated EEG signals consisted in the same oscillatory components with an additional 1/f power law component (Donoghue et al., 2020).

Peaks Extension Method

The *peaks_extension* method is designed to expand an initial set of peaks identified by the *peaks_extraction* method. By calculating the harmonics and subharmonics of the frequency peaks, new ones that reflect the shared harmonicity between peaks can be identified. This method facilitates the expansion of a limited set of frequencies into a more comprehensive collection by examining their inter-harmonic concordance. Its utility lies in the creation of complex tunings, where the number of steps of the tuning are dependent on the number of peaks derived from the original signal.

Computing Harmonicity on Spectral Peaks

The Biotuner features an array of metrics that quantify the harmonic properties of biosignals based on the peaks extracted from the time-series data. Harmonicity, also known as consonance, refers to the pleasantness of musical intervals, which can be assessed through various methods, often by examining the simplicity of their integer ratios (Ferguson, 2011). The primary use of these metrics is to offer novel features for the scientific analysis of biosignals. Additionally, they can be applied to tunings and rhythms derived from spectral peaks, offering a way to quantify their inherent harmonicity. Another application of these metrics is in evaluating consonance over time, which can aid in identifying specific sections of a signal suitable for music generation. All these metrics can be computed by calling the *compute_peaks_metrics* method of the Biotuner object.

Consonance

The consonance value is computed by adding the numerator and denominator of a frequency ratio and dividing its sum by the product of the two (see *Equation 1*).

$$\text{cons} = \frac{x + y}{x \cdot y} \quad (1)$$

Harmonic Similarity

Harmonic Similarity is calculated by averaging the sum of the ratio differences $(x_i + y_i - 1) / (x_i \cdot y_i)$ for a set of $i = 1$ to N frequency pairs (x_i, y_i) , multiplied by 100 (see *Equation 2*), which quantifies the similarity between a dyad of frequencies and their natural harmonic series based on their greatest common divisor, with simpler integer ratios yielding higher values of harmonic similarity and therefore of consonance (Gill & Purves, 2009b).

$$\text{Harmonic Similarity} = \frac{1}{N} \sum_{i=1}^N \left(\frac{x_i + y_i - 1}{x_i \cdot y_i} \right) \times 100 \quad (2)$$

Tenney height

The Tenney height is a mathematical concept used to quantify the consonance or dissonance of musical intervals, chords, or sets of pitches. It is based on the psychoacoustic principle that simpler ratios between frequencies are perceived as more consonant. Higher values indicate increased perceptual dissonance. The Tenney Height computation involves two approaches:

Pairwise Tenney height: This approach calculates the Tenney height for pairs of frequencies by finding the simplest form of their ratio and applying a logarithmic function to the inverse product of the numerators and denominators (see *Equation 3*). This method effectively weights simpler ratios more heavily, reflecting the psychoacoustic perception that simpler ratios tend to be more consonant (Sethares, 2005a).

$$\text{Pairwise Tenney Height (PTH)} = \log_2 \left(\frac{a}{b} \right) \quad (3)$$

Integrated Tenney height: This extended form of the Tenney height calculation considers a set of frequencies as a whole, rather than in pairs. It integrates the prime factors¹⁰ across all the frequencies in the set, applying a logarithmic transformation to the multiplication of these factors (see *Equation 4*). This integrated approach provides a more comprehensive measure of consonance for complex chords, where the interplay of multiple frequencies is essential to the perceived harmonicity.

$$\text{Integrated Tenney Height (ITH)} = \log_2 \left(\prod_{i=1}^n p_i^{e_i} \right) \quad (4)$$

Euler Gradus Suavitatis

The Euler algorithm (Euler, 1739) calculates the degree of dissonance for a given set of frequencies by first converting them to their simplest form, finding the least common multiple (LCM) of the denominators, and then determining the prime factors of this LCM. The "degree of sweetness" is then calculated by summing the primes, subtracting one from each, and adding one to the total sum (see *Equation 5*). A higher Euler value suggests greater dissonance, while a lower value suggests greater consonance.

$$\text{Euler's Gradus Suavitatis (E)} = 1 + \sum_{p \in \text{factors}} (p - 1) \quad (5)$$

¹⁰ Any of the prime numbers that can be multiplied to give the original number.

Subharmonic Tension

The subharmonic tension metric calculates the degree of dissonance introduced by subharmonic¹¹ frequencies (Chan et al., 2019b).

$$\text{Subharmonic Tension (ST)} = \frac{1}{N} \sum_{i=1}^N \left(\frac{\Delta_i}{Sub_i} \right) \quad (6)$$

The Subharmonic Tension (ST) metric takes into account the temporal discrepancies between the occurrences of subharmonic frequencies in a signal (see *Equation 6*). It is calculated by summing the absolute differences in time (Δ), measured in milliseconds (ms), between adjacent subharmonics. Each of these differences is then divided by the corresponding subharmonic frequency value (Sub_i), and the results are averaged over N subharmonics. This average represents the degree of temporal irregularity or 'tension' due to the subharmonics. High ST values indicate poor alignment between the subharmonics of the set of frequencies, leading to increased perceived dissonance.

¹¹ Sequence of frequencies that results from inverting the intervals of the harmonic (overtone) series. Also called the undertone *series*.

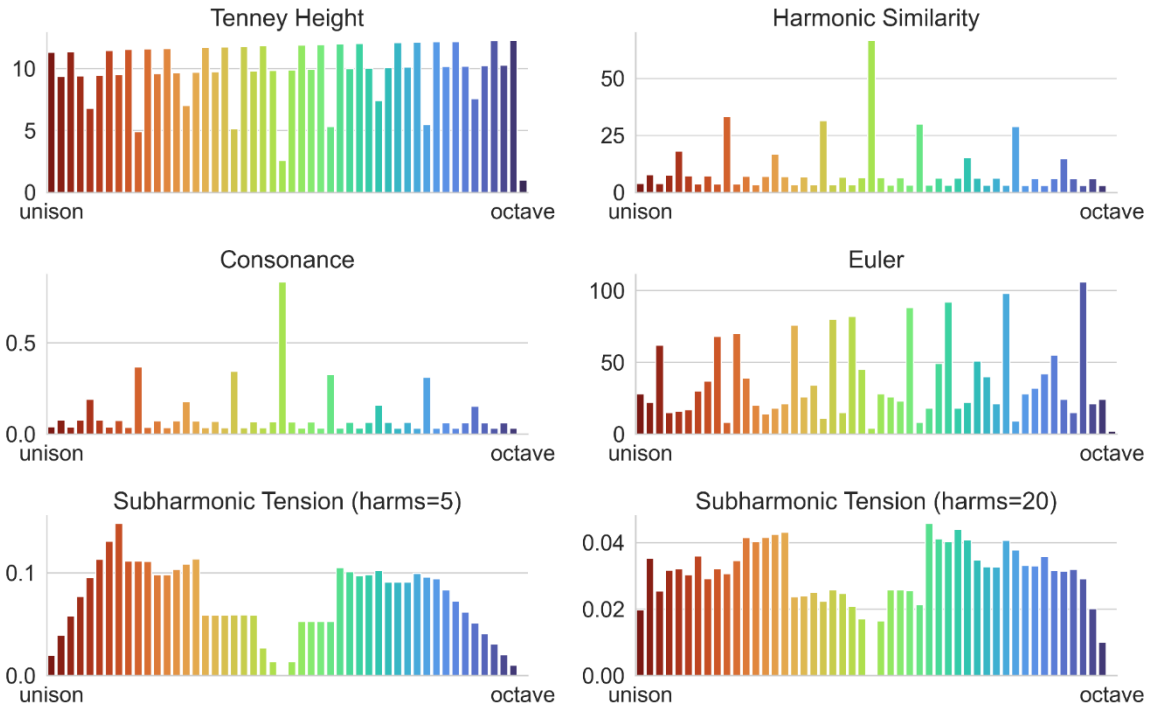


Figure 5.3. Comparative analysis of different metrics evaluated across frequency pairs from unison to octave. The subplots from top-left to bottom-right present Tenney Height, Harmonic Similarity, Consonance, Euler's Gradus Suavitatis, Subharmonic Tension with 5 harmonics, and Subharmonic Tension with 20 harmonics. Each metric assesses a unique aspect of the harmonic or inharmonic qualities, with color gradations representing the transition from unison (left) to octave (right) frequencies.

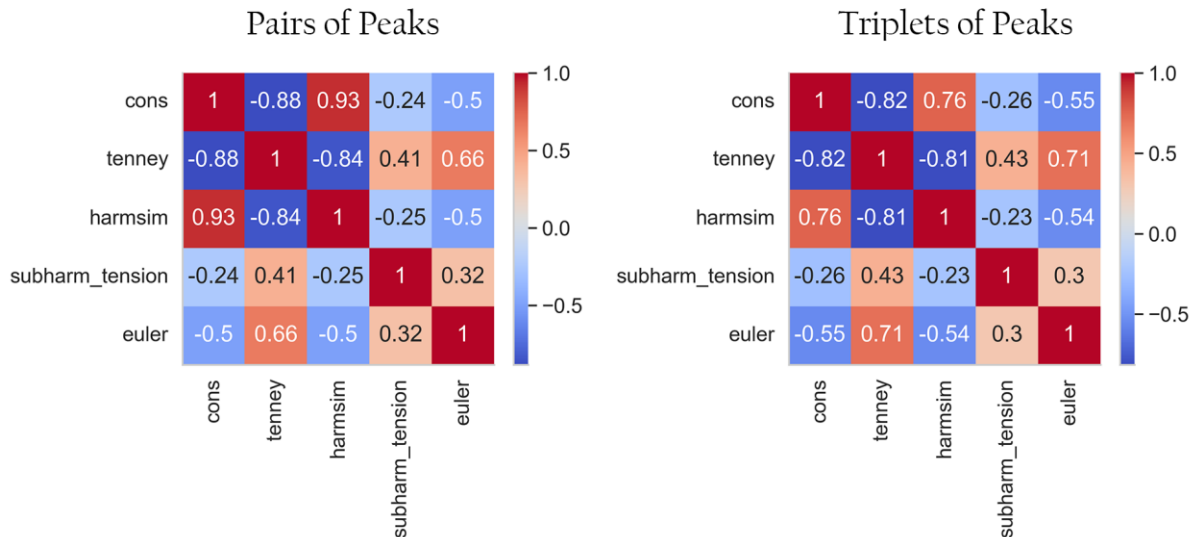


Figure 5.4. Pearson Correlation matrices comparing various metrics across pairs and triplets of peaks.: consonance (cons), Tenney's height (tenney), harmonic similarity (harmsim), subharmonic tension (subharm_tension), and Euler's Gradus Suavitatis (euler). $N = 100$.

Each metric offers a different perspective on the signal's harmonic content, some relying on mathematical purity of intervals, alignment with the harmonic series, or the presence of tension due to subharmonic discrepancies. The complementary nature of these metrics is illustrated by their varying distribution across 100 steps from unison to octave (refer to **Fig. 5.3**), and by the correlation matrices with Pearson r values ranging from 0.23 to 0.91 (see **Fig. 5.4**). Importantly, for the Tenney height, subharmonic tension and Euler metrics, higher values correspond to increased dissonance, clarifying the reason behind the mix of positive and negative correlations. The correlation matrices also highlight that the relationships between different harmonicity metrics are generally consistent when comparing pairs and triplets of peaks. However, an exception is noted in the case of harmonic similarity and consonance, which exhibit a high correlation for pairs of peaks but a lesser correlation for triplets.

Integration with MNE-python

Harmonicity metrics can be computed directly on MNE epochs objects (Gramfort et al., 2013), which allows to easily analyze M/EEG data and compare harmonicity across different conditions. For that purpose, the *biotuner_mne* function of the *biotuner2d* module can be used, as seen in this example:

```

# Import necessary modules
import mne
from mne.datasets import multimodal
from mne import make_fixed_length_events
from biotuner.biotuner2d import biotuner_mne

# load the data
raw_file = str(multimodal.data_path().joinpath('multimodal_raw.fif'))

# Load the raw data
raw = mne.io.read_raw_fif(raw_file, preload=True)

# Create events
events = make_fixed_length_events(raw, start=0, stop=None, duration=2.0)

# Epoch the data
epochs = mne.Epochs(raw, events, tmin=0, tmax=2, baseline=None, preload=True)

# Define the biotuner parameters
bt_dict = {
    'peaks_function': 'EMD',
    'sf': raw.info['sfreq'],
    'precision': 1,
    'fmin': 2,
    'fmax': 90,
    'n_peaks': 5,
    'harm_thresh': 30,
    'delta_lim': 100,
}

# Compute biotuner metrics on epochs file
bt_df = biotuner_mne(epochs, bt_dict, savefile=True, savename='multimodal_raw')

```

Time-resolved harmonicity

The *time_resolved_harmonicity* method is designed for the dynamic assessment of consonance and dissonance as they evolve over time, making it particularly effective for signals with varying harmonic content. This method utilizes Empirical Mode Decomposition (EMD) to decompose a signal into various Intrinsic Mode Functions (IMFs), isolating different frequency components. Within this method, two distinct modes are employed. The first mode involves extracting instantaneous frequencies¹² (IFs) from these IMFs using the Hilbert-Huang transform¹³ (Huang & Wu, 2008). Subsequently, it measures the harmonicity among these IFs at each

¹² The rate of phase change in a signal at any moment, showing how its frequency content changes over time.

¹³ A technique for time series analysis, particularly effective for non-linear and non-stationary data. It applies the Hilbert Transform to the components obtained from Empirical Mode Decomposition, providing a detailed instantaneous frequency and amplitude analysis.

temporal point (see **Fig. 5.5**). The second mode, termed 'SpectralCentroid', employs spectromorphological analysis¹⁴ to calculate the spectral centroid¹⁵ of each IMF over time (Smalley, 1997). Then, it assesses the harmonicity between the spectral centroids of all IMFs at each moment. Any of the previous harmonicity metrics can be used to compute time-resolved harmonicity. This method simultaneously computes harmonicity across time (see **Fig. 5.5**) and identifies *spectral chords* (see **Fig. 6**) based on moments of high consonance. Therefore, spectral chords correspond to the sets of IFs or spectral centroids for moments where harmonicity exceeds a predetermined threshold, providing chord progressions matching the harmonic content of biosignals.

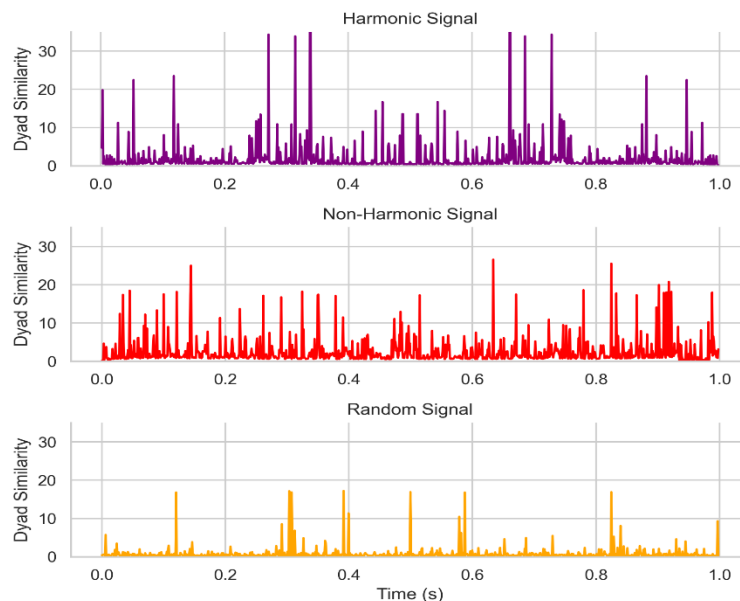


Figure 5.5. Time-resolved harmonicity using instantaneous frequencies for three different types of signals. (a) Harmonic signal ($f_{reqs} = 10, 15, 20$) characterized by a consistent and periodic pattern in dyadic similarity. **(b)** Non-harmonic signal ($f_{reqs} = 10, 18.2, 33.5$) with sporadic peaks, indicating less regularity in frequency relationships. **(c)** Random signal with a highly irregular dyadic similarity pattern, highlighting the absence of structured harmonic relationships.

¹⁴ Analysis of sound focusing on the evolution of its spectral properties and shapes, useful in studying sound textures and timbres.

¹⁵ A measure indicating the 'center of mass' of a sound's spectrum, associated with its perceived brightness.

Signals used in **Figure 5.5** were generated by summing oscillatory signals of either harmonic or non-harmonic frequencies, while the random signal was generated with random numbers and filtered around the range of frequencies of the two other signals. Harmonic signals exhibit moments of high harmonic similarity, as expected, with a symmetric pattern, while non-harmonic signals reveal less structure in the temporal evolution of harmonic similarity, with still higher harmonic similarity than random signal.

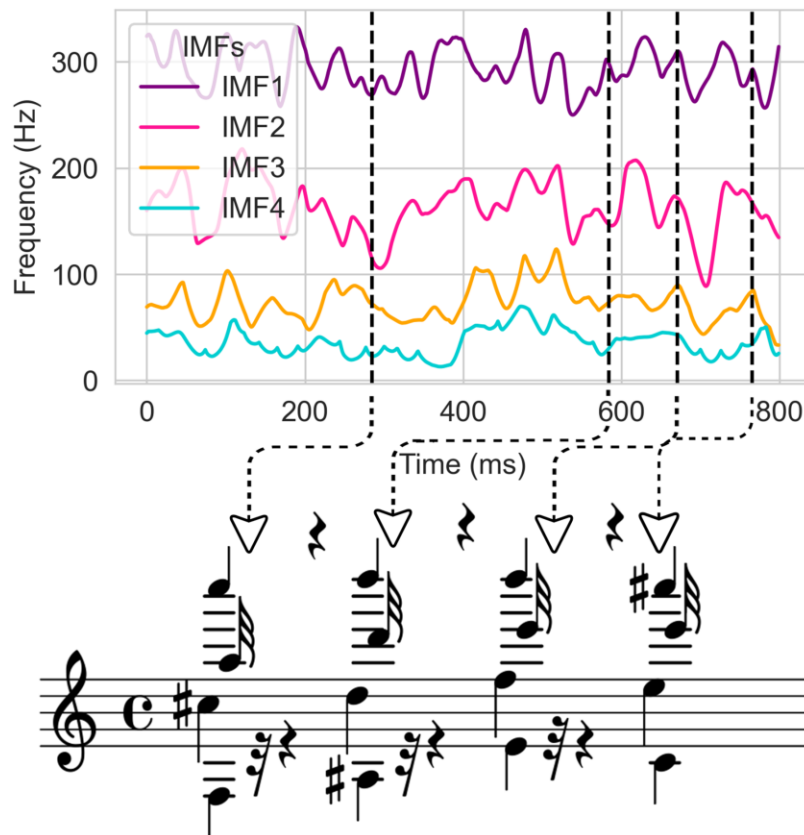


Figure 5.6. Identification of spectral chords using time-resolved harmonicity. The top panel represents the instantaneous frequencies (IFs) of each IMFs, with dashed lines corresponding to moments of high harmonic similarity between all pairs of IFs. The bottom panel illustrates the corresponding musical notation of the identified spectral chords.

Scale Construction method

The Biotuner Toolbox offers a scale construction module that translates the mathematical relationships of peaks into musical scales. This approach is rooted in the analysis of harmonic interactions within biosignals, drawing extensively on techniques primarily from music theory. The process transcends mere artistic interpretation of mapping peaks to pitches; it serves as a psychoacoustic structural framework (microtuning) that alters the music's overall timbre based on these peaks and their interrelations. The more harmonious the signal, the more consonant the resulting tuning system. This approach aims to create an effective, perceptible, and comprehensible musical map of the brain signal.

Peaks Ratios

This scale corresponds to the ratios between identified peaks from the signal's frequency spectrum. By rescaling the ratios between the unison (1:1) and the octave (2:1), a set of ratios that can be directly mapped onto a musical tuning. The peaks ratios are computed by default when calling the *peaks_extraction* method.

Dissonance Curve (*compute_diss_curve*)

The dissonance curve reflects how the combination of different frequencies can produce varying degrees of consonance and dissonance (Sethares, 2005a). By graphing perceived dissonance across different frequency pairs, one can establish a scale based on intervals that correspond to the local minima on the curve, which are points where the dissonance is less than the immediate surrounding values (see **Fig. 5.7a**). These curves facilitate the generation of scales that are harmonically compatible with the timbral characteristics of the sound source.

Harmonic Entropy (*compute_harmonic_entropy*)

Harmonic entropy is a measure of the uncertainty in pitch perception, and it provides a physical correlate of tonalness, one aspect of the psychoacoustic concept of dissonance (Sethares, 2005a). High tonalness corresponds to low entropy and low tonalness corresponds to high entropy. Harmonic entropy can be represented across intervals from unison to octave (see **Fig. 5.7b**) to construct the scale from local minima.

Harmonic Tuning (*harmonic_tuning*)

Harmonic tunings correspond to sets of ratios that are derived from dividing harmonic positions (whole numbers) iteratively until the ratio falls between the unison (1:1) and the octave (2:1). Harmonic positions can be extracted by two different ways with the Biotuner, either by using the *harmonic_recurrence* peaks extraction method or by using the *harmonic_fit* peaks extension method.

By combining these methods, the Biotuner constructs scales that can then be used in various applications, from scientific analysis to music composition, with the aim of providing an insightful bridge between the structure of biosignals and the aesthetics of music tuning systems.

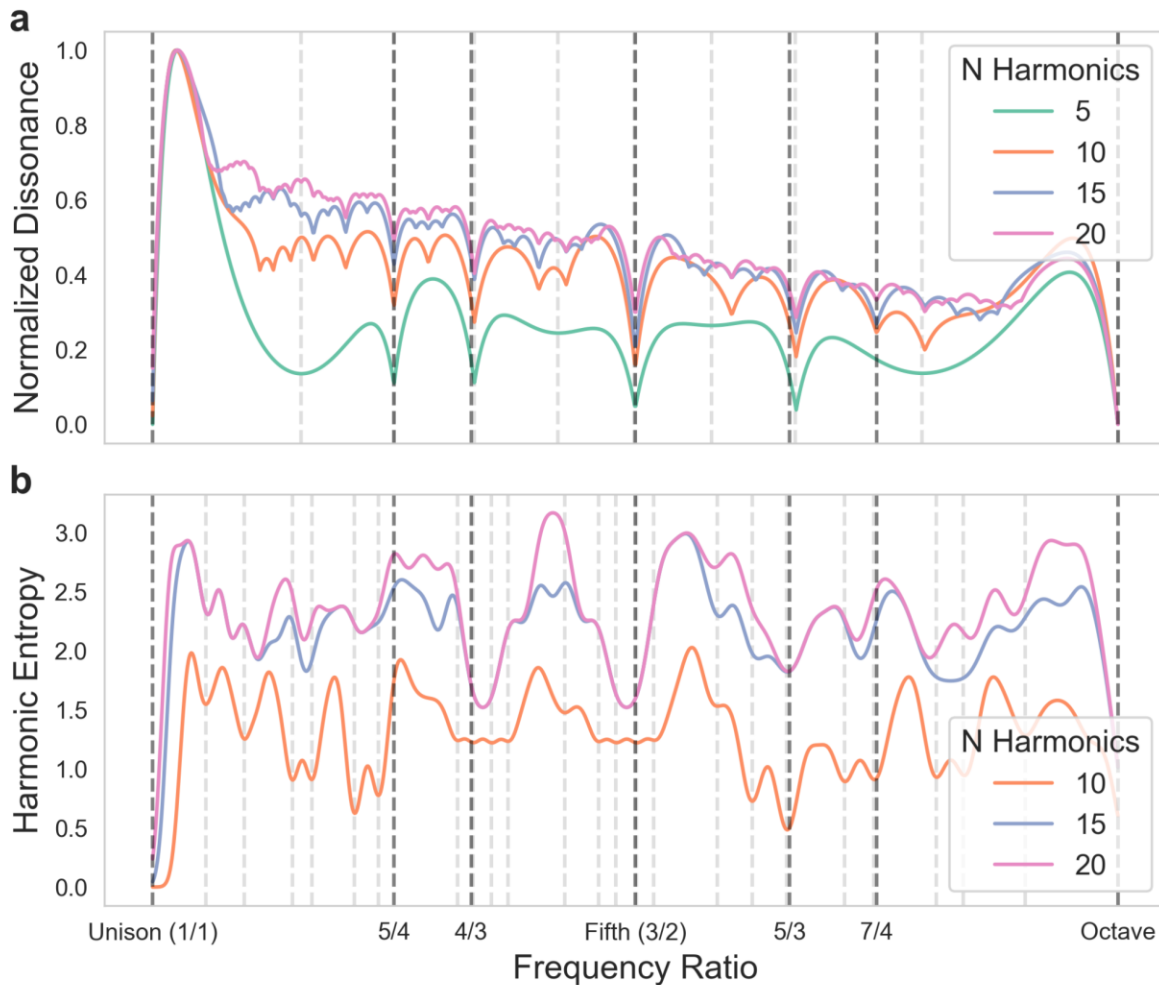


Figure 5.7. Comparison of Normalized Dissonance and Harmonic Entropy Across Different Sets of Harmonics. (a) Normalized dissonance curves for sets of 5, 10, 15, and 20 harmonics. Each curve represents the perceived dissonance between pairs of tones within the respective harmonic set, plotted against the frequency ratio. (b) Harmonic entropy for the sets of harmonics (10, 15, 20), reflecting the tonal consonance as a function of the frequency ratio. Peaks in the harmonic entropy curves correspond to frequency ratios with higher degrees of complexity and dissonance. The set of 5 harmonics was removed since not enough ratios were generated to provide a meaningful harmonic entropy curve. In both subplots, gray vertical lines correspond to scale steps (i.e. local minima) and black vertical lines to simple integer ratios labeled on the x-axis.

Rhythm Construction method

Rhythm is another musical parameter that can be representative of the harmonicity levels of the brain signal in a directly musically comprehensible manner. Indeed, frequency relations, which characterize microtonal structures, can be expressed as rhythmic structures by translating frequency ratios into temporal intervals, thereby mirroring the signal's harmonic content in

rhythmic patterns. [...] Euclidean rhythms are one way to simplify complex frequency relationships from brain signals into perceptually coherent rhythmic patterns. The *rhythm_construction* method allows for the generation of Euclidean rhythms from a given musical scale (ratios between 1/1 and 2/1). Euclidean rhythms are defined by the equal distribution of a number of pulses (hits) across a specified number of steps (Toussaint, 2005). This method uses the numerators of ratios as the number of steps and the denominators as the number of hits, ensuring that the ratio's denominator does not exceed a predefined maximum. It offers two distinct modes of operation: the *'default'* mode, where each ratio is directly converted into a corresponding Euclidean rhythm, and the *'consonant'* mode, which focuses on maximizing the consonance among all possible rhythm pairs. In the *'consonant'* mode, a consonance threshold is set, and common denominators are used to enhance the uniformity in the distribution of steps across various rhythms, thereby ensuring a harmonious rhythmic output. The *'max_denom'* argument offers control over the maximum number of steps in each rhythm (see **Fig. 5.8**).

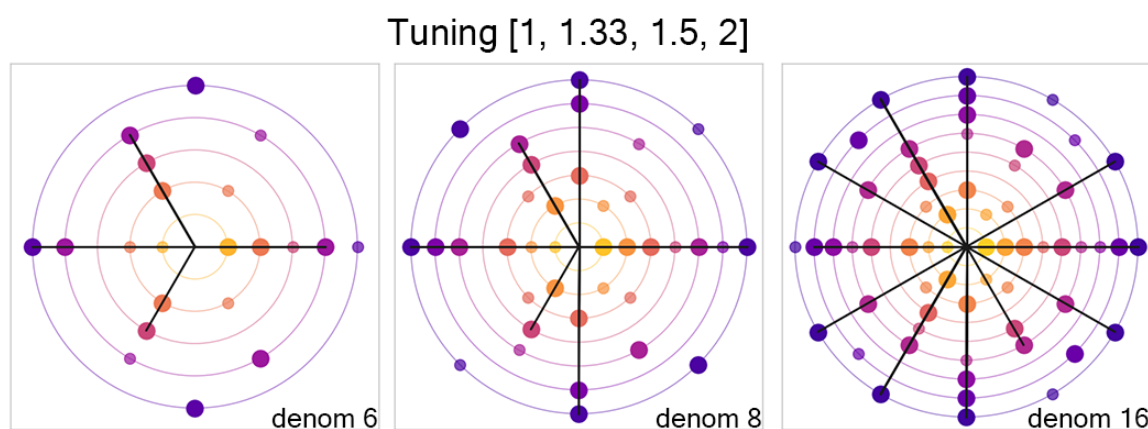


Figure 5.8. Visualization of Euclidean rhythms with varying maximal denominators. The rhythmic patterns produced with a tuning series [1, 1.33, 1.5, 2] across different maximal denominators (6, 8, and 16). Small dots correspond to steps without pulses and bigger dots to steps with pulses.

Other Objects to explore Harmony across Time, Sensor-Space / Individuals and Spectrum

Transitional Harmony (*object*)

Transitional harmony, as implemented in the *transitional_harmony* class, offers a novel approach to understanding the dynamic evolution of harmonic structures within a time series, making use of the Biotuner Object within a higher-level programming structure. Leveraging subharmonic progressions, this method evaluates the tension between successive temporal windows of data. By extracting subharmonics of spectral peaks and evaluating the closest common subharmonics in consecutive timeframes, transitional subharmonic tension can be quantified (Chan et al., 2019b). In contrast to stationary harmony which focuses on the properties of individual chords or sonorities, transitional harmony provides a computational framework for analyzing the movement and relationship between chords over time. In the context of music, transitional harmony allows for a deeper exploration of chord progressions, enhancing our understanding of how compositions achieve emotional impact through tension and resolution (Chan et al., 2019b). Here, I demonstrate its application to the analysis of biosignals, suggesting its utility in detecting subtle changes in biological rhythms. This application may enhance our ability to interpret transitions in physiological states.

The methodology offers two distinct modes: one employs overlapping windows with peak extraction for each segment, while the other utilizes instantaneous frequencies (*see time-resolved harmonicity subsection*) to gauge time-resolved transitional harmony. The flexibility in window overlap and the precision of peak analysis facilitate a granular examination of harmonic relationships.

Transitional harmony is demonstrated for both musical signals (**Fig. 5.9a**) and simulated electrocardiogram (ECG) signals (**Fig. 5.9b-c**). The utilization of simulated ECG signals facilitated

control over specific properties of the signal, thereby simplifying the interpretation of transitional harmony across various sets of generated signals. For musical signals, a sequence following the I-IV-V-I progression was created using the chords 'C', 'F', and 'G'. Transitional harmony was calculated across one-second windows with a substantial 90% overlap, enabling detailed temporal analysis. **Figure 5.9a** illustrates the escalation of tension during the transition to the IV and V chords, followed by the expected resolution upon returning to the I chord. **Figure 5.9b** presents the transitional harmony of ECG signals generated at 120 beats per minute for three different levels of heart rate variability¹⁶ (Makowski et al., 2021), which is known as a physiological marker of cardiac coherence and autonomic nervous system balance (Thayer et al., 2012; Shaffer & Ginsberg, 2017). This analysis reveals the nuanced interplay between heart rate variability and transitional harmony, offering insights into the rhythmic patterns that underlie cardiac function. The visualization aims to demonstrate that variations in heart rate are captured by transitional harmony metrics. As expected, the average transitional subharmonic tension is notably higher for ECG signals with greater heart rate variability.

¹⁶ The fluctuation in the time intervals between adjacent heartbeats.

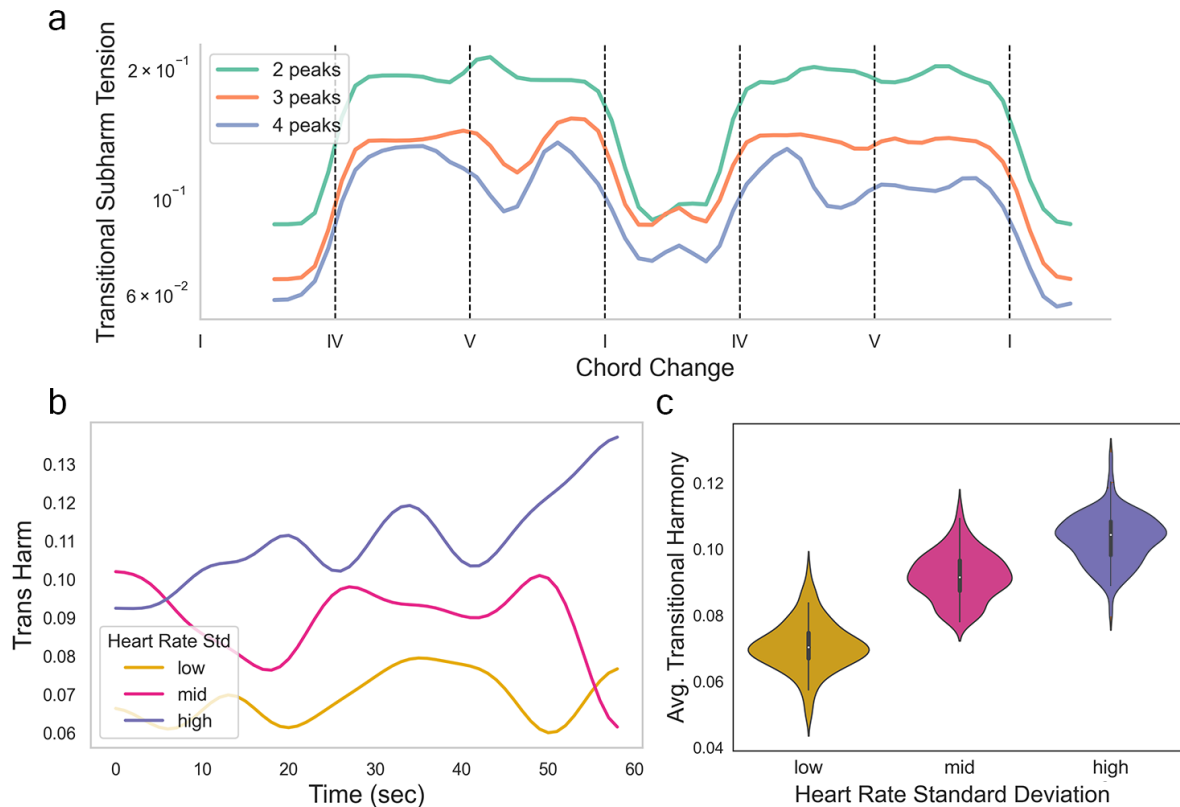


Figure 5.9. Transitional Subharmonic Tension in Classical Chord Progression and Across Heart Rate Variability Conditions. (a) Comparative analysis of transitional subharmonic tension for the chord progression *I, IV, V, I* computed for sets of 2, 3 and 4 peaks. (b) Smoothed transitional harmony over a 60-second duration for ecg simulated signals with three heart rate variability conditions: 'low' (std = 1), 'mid' (std = 15), and 'high' (std = 30). (c) Distribution of average transitional harmony values calculated from 100 bootstrap samples, highlighting the variance within each heart rate standard deviation category

Harmonic Connectivity (*object*)

The `harmonic_connectivity` class extends the application of harmonic analysis to explore the relationships between multiple time series, typically originating from different sensors or electrodes. In neuroscience, understanding network dynamics through connectivity is increasingly seen as key to unraveling complex brain functions (Chiarion et al., 2023; Imperatori et al., 2018; Stam & van Straaten, 2012). This class, building on the Biotuner Object, offers new connectivity metrics specifically designed for assessing harmonicity between sensors or any set of signals and incorporates previously discussed peaks metrics within a multivariate context.

Rhythmic Ratio Coupling with Imaginary Component (RRCi):

This metric provides insights into the temporal coupling between signals by examining the imaginary components¹⁷ of the complex phase relationships at each pair's peak frequencies. Lower values indicate less complex phase-coupling relationships.

$$RRCI = \left| \frac{1}{N} \sum_{t=1}^N \Im \left(e^{j \cdot (n \cdot \phi_1(t) - m \cdot \phi_2(t))} \right) \right| \quad (7)$$

This proposed formula computes the index by calculating the average magnitude of the imaginary component of the complex exponential phase differences between two signals. These phase differences are weighted by their respective rhythmic ratio components, n and m , and averaged across all time points $t= 1, \dots, N$, where N denotes the total number of time points. The instantaneous phases of the signals at frequencies f_1 and f_2 are represented by $\phi_1(t)$ and $\phi_2(t)$, respectively. This approach extends the capabilities of phase-based connectivity analyses by facilitating the examination of phase coupling between non-equivalent frequencies, thereby providing a more detailed understanding of complex interactions in oscillatory networks.

Weighted Phase Lag Index for Cross-Frequency (wPLI_crossfreq):

This phase synchronization metric assesses the phase relationships between different frequency components of two time series. It is an extension of the classical weighted phase lag index¹⁸ (Hardmeier et al., 2014), with the particularity of being computed between different

¹⁷ The imaginary component of a complex number represents the extent of rotation from the real axis in the complex plane, often used in signal processing to capture phase information.

¹⁸ Measure that quantifies the consistency of phase differences between signals, giving more weight to phase leads or lags that are consistent across time.

frequency bands. Similar to RRCi, this metric offers the advantage of tackling *polyrhythmic phase-coupling*¹⁹.

In addition to these unique metrics, the *harmonic_connectivity* class can apply all the peaks metrics discussed earlier, such as *harmonic_similarity*, *euler*, *consonance*, *tenney*, and *subharmonic_tension*, to the context of multivariate data. These metrics, initially described for individual time series, are adapted to compute the interrelationships between pairs of time series.

Figure 5.10 illustrates the behavior of harmonic connectivity metrics and classical wPLI between three harmonic and one non-harmonic signals.

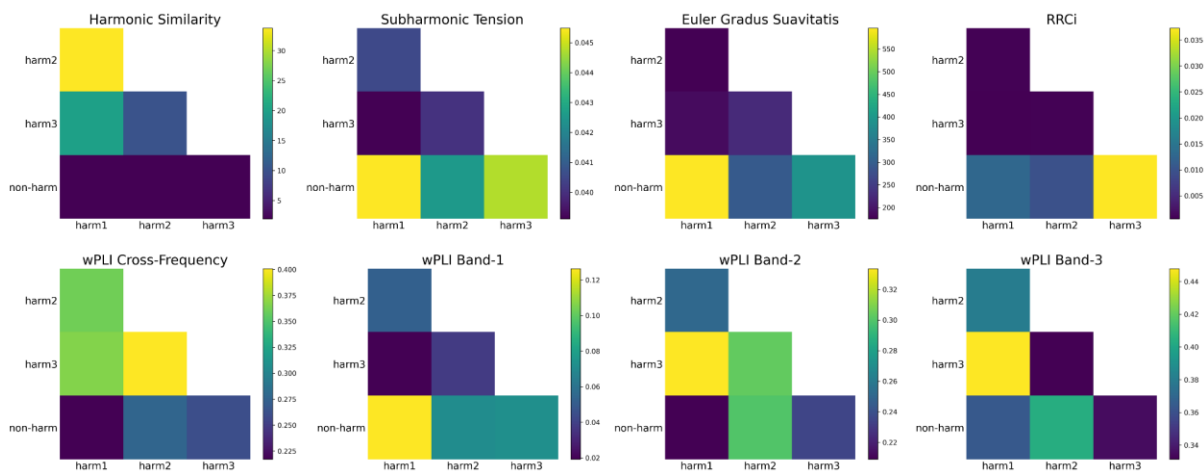


Figure 5.10. Comparative analysis of harmonic connectivity and classical weighted Phase Lag Index (wPLI) metrics on simulated signals. The matrices display the interrelationships between three harmonic signals (harm1, harm2, harm3) and one non-harmonic signal (non-harm). The bottom rows of the matrices (non-harmonic signal coupled with harmonic signal) consistently show lower harmonic connectivity compared to connectivity between harmonic signals, which means that the metrics properly capture harmonic relations between signals. Classical wPLI, which is not designed to assess harmonic relationship, fails to exhibit this pattern. Frequencies used for the generated signals: *harm1*: (20, 30, 40), *harm2*: (25, 35, 45), *harm3*: (22, 32, 42), *non-harm* (20.5, 32.1, 38.3). Each of the three peaks were falling within each of the three fixed frequency bands used to extract the peaks from the signals. The bands were [15, 26], [26, 36], [36, 46].

¹⁹ Involves any type of phase-coupling between two non-equal frequencies (n:m).

Harmonic Spectrum (*object*)

The harmonic spectrum is a module of the Biotuner that provides a way to assess the harmonic weight of each frequency in a signal, taking into account both its harmonic relationships with other frequencies and its power contribution to the overall spectrum.

$$H_{\text{spec}}(f) = \sum_{f_i \neq f} \text{DyadSim}(f, f_i) \cdot \text{Pow}(f) \cdot \text{Pow}(f_i) \quad (8)$$

The *formula 8* for the harmonic spectrum determines the harmonicity of each frequency, f , within a signal by considering both its power and its harmonic relationships with other frequencies. To calculate this, for a given frequency, f , the formula sums the dyadic similarity, $\text{DyadSim}(f, f_i)$, between frequency f and each different frequency f_i , and then multiplies this by the power of frequency f and the power of frequency f_i . This process is repeated for all unique frequency pairs where f is not equal to f_i . The value of $H(f)$ is normalized by dividing it by the total power. The outcome, the harmonic spectrum, can be used to identify significant spectral peaks, and calculate various metrics like averaged harmonicity, spectral flatness, and spectral entropy, giving a nuanced view of the signal's harmonic complexity. **Figure 5.11** illustrates how computing the harmonic spectrum effectively highlights harmonic structures within a signal.

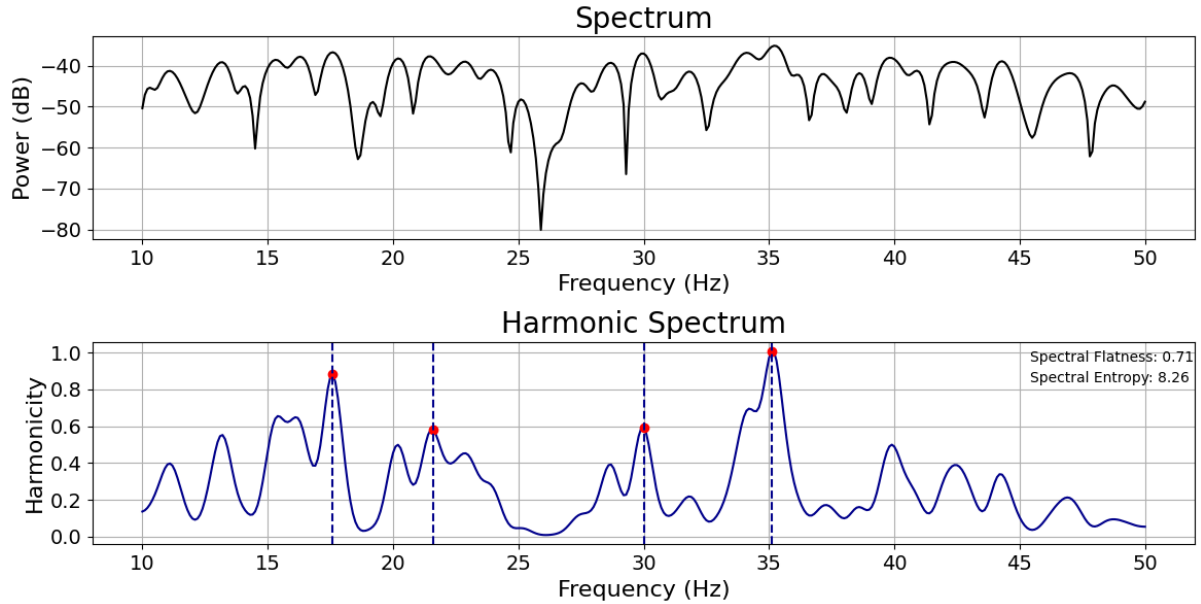


Figure 5.11. Harmonic Spectrum. Top panel displays the power spectrum of a signal with frequency plotted against power in decibels (dB). The bottom panel shows the corresponding smoothed harmonic spectrum, where harmonicity values are plotted against frequency. Notable spectral peaks are marked by red dotted lines. Prominence parameter of peak extraction can be adjusted. The metrics in the top right corner of the harmonic spectrum indicate the Spectral Flatness (0.71) and Spectral Entropy (8.26), quantifying the uniformity and complexity of the distribution of harmonic power among spectral components, respectively.

Discussion

Practical applications

The Biotuner Toolbox, with its novel approach of integrating music theory and signal processing, presents a diverse range of applications across different fields. These applications could enhance scientific research, while extending into artistic and creative realms. Its functionality encompasses the analysis of human-originated signals, including Electrocardiogram (ECG), Electromyogram (EMG), and Electroencephalogram (EEG), providing detailed insights into cardiac, muscular, and neural activities, respectively. Beyond human data, it can process biosignals from non-human entities, such as the electrophysiological patterns observed in plants and mycelium networks. These capabilities allow for an in-depth exploration of both human and non-human biological processes. Its versatility extends to interpreting geophysical and

astrophysical data, including seismic, anemometric, and gravitational wave information. The Biotuner's capacity to sonify these diverse data sets transforms complex natural phenomena into auditory experiences, making them accessible for educational, engagement, and creative purposes. In the realm of oscillatory coupling, the Biotuner offers insights into the interconnectedness of various physiological systems within an individual, such as heart-brain synchrony. This understanding has significant implications for comprehending health and behavioral patterns. Moreover, the Biotuner's application in analyzing harmonic interactions between individuals opens new possibilities for exploring social dynamics and collective behaviors, not only in humans but potentially in other species as well. Another crucial application lies in extending the methodologies of cognitive neuroscience. It introduces new harmonicity metrics that provide a fresh lens through which various states of consciousness can be examined, offering new insights into brain function during different cognitive and emotional states. Furthermore, these metrics can be correlated with phenomenological measures, paving the way for a deeper understanding of the neural basis of consciousness and subjective experiences.

Code availability and resources

The code of the Biotuner is accessible openly on Github:

<https://github.com/antoinebellemare/biotuner>.

More extensive documentation of the API and several notebooks of examples can be consulted

here: <https://antoinebellemare.github.io/biotuner/>.

A notebook containing the code to reproduce all the figures of this paper is also made available:

https://github.com/AntoineBellemare/biotuner/blob/main/docs/examples/toolbox_paper_notebook/Figs_biotuner_toolbox_paper.ipynb

Conclusion

The Biotuner Toolbox, a pioneering open-source python toolbox, epitomizes the convergence of neuroscience, music theory, and signal processing. Its core functionality lies in its ability to apply musical concepts such as harmony, rhythm, and scale construction to the analysis of biosignals. This unique approach offers a fresh perspective on the study of brain oscillations and their harmonic properties. The toolbox's structure is meticulously designed to handle various signal types, from neural recordings to environmental and physiological data, through its versatile `biotuner_object`. The Biotuner Toolbox exemplifies the significance of transdisciplinary work in fostering innovation and generating new research fields. By integrating principles from music theory into neuroscience, it opens untapped possibilities for analyzing and interpreting complex biosignals. This integration not only enhances scientific research but also extends its utility to artistic realms, enabling creators to translate natural rhythms and patterns into musical compositions. Such a cross-disciplinary approach is crucial for driving forward both academic and creative explorations, broadening the horizons of how we perceive and interact with the world around us.

General discussion

The discussion section of this thesis follows the order of the main chapters and encapsulates their central findings. Initially, it provides a concise summary of these findings. Subsequently, it delves into the significant contributions of the research, discussing how divergent perception relates to creative cognition as well as the application of theories of harmonicity to the study of biological processes. In concluding this section, the insights from the emergent nexuses segment highlight the experimental paradigm's applicability beyond visual pareidolia to auditory modality, its potential in investigating machine pareidolia and in exploring how brain-computer interfaces may enhance creative processes. These future directions highlight the impending intersections among computational neurosciences, phenomenology, and digital arts.

Summary of the findings

Structured into two principal segments, the thesis first addressed pareidolia, investigating it as a manifestation of divergent perception—essentially the perceptual analogue of divergent thinking. This investigation was detailed across the initial three chapters. The latter two chapters shifted focus to an exploration of music creation derived from EEG signals. This exploration leveraged bioharmonic structures, facilitating the emergence of microtonal and polyrhythmic formalisms. The purpose of this approach was to delve into auditory multi-stability within a research-creation framework.

In this thesis, the fundamental research component introduced a novel methodological approach to studying divergent perception. The initial chapter laid the theoretical groundwork for investigating divergent perception, proposing that aberrant salience is crucial in the development of pareidolic perception and creativity. The connection between the creative aspects of psychosis and psychedelic experiences with divergent perception was explored, alongside experimental

strategies for probing unconstrained pareidolia. Subsequently, a behavioral study was conducted, illustrating a correlation between creativity (measured through self-reports and objective assessments) and the occurrences and number of pareidolic perceptions. This study also uncovered that individuals with higher creative abilities experience pareidolia across a broader spectrum of fractal dimensions. Further, the neural correlates of pareidolia were investigated using Magnetoencephalography (MEG), revealing that the experience of pareidolic perceptions is associated with alterations in oscillatory power and that the link between stimulus fractal dimension and brain fractal dimension is influenced by the intensity of pareidolic experience.

The research-creation segment of the thesis, encompassed in chapters four and five, presented evidence supporting the role of harmonic structures in brain signals and techniques for the derivation of musical structures from these physiological activities, introducing the concept of neuro-musical isomorphisms. This segment established methodological connections between music theory and computational neuroscience, leading to the development of biologically driven tuning systems and rhythms, metrics for the computation of bioharmonicity, and an implementation of transitional harmony. It was also proposed that Bayesian frameworks could be instrumental in the design of innovative brain-computer interfaces. The concluding chapter offered a more technical exposition of the *Biotuner Toolbox*, a Python package providing resources for researchers and artists to explore brain dynamics' harmonicity and create music based on biosignals.

Sensory ambiguity as a source of creative exploration

This section summarizes the main contributions of this thesis to the field of the neuroscience of creativity and to the cross-fertilization of music theory and biosignals analysis. It introduces divergent perception as a key to understanding creative cognition and outlines the theoretical, behavioral, and electrophysiological evidence linking statistical properties of visual

stimuli and creativity to pareidolic perception. Additionally, it explores innovative methods for generating musical structures from biosignals, suggesting that biology (and by extension ecosystems) can be the source of creative artifacts.

Divergent perception is associated with divergent thinking

The traditional view of creativity has often been limited to its expression through divergent thinking (Dietrich, 2004; Kim, 2006; Reiter-Palmon et al., 2019), defined as the ability to generate multiple solutions to a problem. This thesis, however, expands this view by introducing and exploring the concept of divergent perception. Divergent perception, as revealed through our research, offers a perfect context to study interactions of top-down and bottom-up processes in perceptual emergence. It is characterized by an individual's capacity to perceive recognizable forms within ambiguous or complex stimuli, a phenomenon known as pareidolia.

Central to the findings is the empirical evidence that creativity correlates with the propensity to experience pareidolia. Individuals with higher levels of creativity, quantified through both a self-reported measure of phenomenology of the creative process and the Divergent Association Task (DAT), were observed to experience pareidolia more often and in a wider range of stimulus fractal dimensions. Creativity was correlated with specific aspects of pareidolic perception, particularly the fluency (the number of percepts identified) and flexibility (the ability to perceive percepts across diverse stimuli).

The research also underscores the importance of the fractal dimension and contrast of visual stimuli in influencing and manipulating pareidolic perception. It was found that stimuli with intermediate fractal dimensions and higher contrasts were more likely to induce pareidolia, especially in individuals with lower creativity scores, whereas high-creatives reported pareidolia across a wider range of fractal dimensions. It suggests that the interplay between an individual's creative capacity and the sensory characteristics of their environment can significantly influence

their perceptual experiences. This finding points to the potential of external sensory inputs in either enhancing or moderating creative perception, offering new avenues for research in perceptual and cognitive psychology of creativity. Additionally, the implications of these findings for creativity assessment and training are significant. The clear link between divergent perception and divergent thinking posits pareidolia not just as an interesting psychological phenomenon but as a potential metric for assessing and nurturing creativity.

Fractality of visual stimuli interacts with pareidolic experiences in predicting fractality of brain dynamics

This research introduced the concept of *fractality matching*, which refers to the relationship between the fractal dimension of visual stimuli and the fractality in brain dynamics, as measured by different methods assessing signal persistence and memory (Hurst exponent, DFA), as well as irregularity and complexity (Sevcik and Petrosian) of the signal. Cognitive neuroscience research has recently brought forth the idea of complexity matching (Carpentier, 2020), where the complexity of external stimuli is mirrored by the complexity of neural signals. This thesis extends this concept by specifically examining the fractality, which is a measure of the scale-invariance, computable on 2D matrices (e.g. visual stimuli) and time series (e.g. neural responses).

What sets the findings apart is the discovery of a significant inverse relationship between the fractal dimension of visual stimuli (box-counting method) and the fractality of brain signals in visual areas. This inverse fractality matching indicates that as the geometric complexity of the stimuli increases, certain areas of the brain exhibit less complex signal patterns. Most intriguingly, this relationship is modulated by pareidolia, where higher frequencies of pareidolic experiences shift this fractality matching to a positive correlation. In other words, when individuals experience more pareidolia, the brain's signal complexity more closely matches the complexity of the stimuli.

In a broader context, the results on fractality matching contribute to the ongoing discussion about how brain neural signatures mirror and interact with bottom-up sensory information, suggesting that the brain's response to external stimuli is a dynamic and adaptive process that can be assessed using scale-free measurements of brain dynamics. This adaptability might be a fundamental characteristic of neural computation, enhancing the brain's capacity for efficient information processing and adapting to altered perceptual states (Moss et al., 2004; Taylor & Spehar, 2016).

These results highlight the importance of considering the fractal nature of both stimuli and brain dynamics to understand cognitive processes. It opens new pathways for research in areas such as artificial intelligence, where understanding the principles of fractality matching could inform the development of more sophisticated neural network models that could synchronize to humans using biofeedback systems and different forms of complexity matching.

Biosignals as embodied musical structures

This thesis introduced concepts and methodologies at the confluence of neuroscience, music theory, and phenomenology. An integration of the concept of harmonicity to the broader context of brain dynamics was detailed, presenting supporting evidence from different clusters of the literature, drawing parallels between these fields, and finding tangible applications. I brought to light the integral role of harmony and resonance in both biological systems and musical compositions, reviewing theories such as the Binary Hierarchy Brain Body Oscillation Theory (Klimesch, 2018b) and the General Resonance Theory of Consciousness (Hunt, 2020; Hunt et al., 2019). The exploration of bioharmonies was also supported by the neuronal model of consonance which hypothesizes a matching between harmonics structures in sensory input and corresponding frequency structure in brain signals (Bidelman & Krishnan, 2009; Lerud et al., 2014)(Bidelman & Krishnan, 2009; Lerud et al., 2014). These models underscore the importance

of harmonicity in neural communication and integrative functions. I introduced computational models that analyze harmonicity in biosignals, tackling nested harmonic structures in brain dynamics and their translation into musical systems.

I demonstrated that brain signals exhibit harmonic properties measurable as arithmetic ratios of spectral peaks, drawing from the concepts of stationary and transitional harmony in music theory and applying them to biosignals. I also introduced new sonification methods for dynamic tuning construction, Euclidean rhythms generation and identification of spectral chords from brain signals. These methods, when integrated in real-time feedback loops, enable the generation of music that reflects the endogenous harmonic structure, offering a novel approach to model brain and phenomenological transitions. This work significantly contributes to the practical application of these theoretical concepts through the development of the *Biotuner* Toolbox, demonstrating the practicality of the presented theoretical concepts. Moreover, I proposed experimental protocols and models to study resonance and harmonicity in human-machine interactions. This opens new avenues for both artistic expression and scientific inquiry. This exploration simultaneously enhances our understanding of brain dynamics while opening new perspectives in musical composition and perception.

In conclusion, the two last chapters contribute a unique blend of scientific innovation and creative exploration, presenting new ideas at the intersection of neuroscience, music theory, and phenomenology. I propose an original perspective on understanding and utilizing the harmonic structures inherent in brain dynamics, by enhancing traditional signal processing techniques in computational neuroscience with models of harmonicity. Simultaneously, this approach offers musical compositional tools that leverage the inherent complexity of biological processes to explore new musical formalisms.

Emergent Nexuses

This ultimate section explores potential future converging paths of scientific inquiry, artistic creativity, and technological innovation, underscoring the timeliness of interdisciplinary approaches. The term *Emergent Nexuses* signifies the dynamic intersections (*nexuses*) across diverse disciplines, emphasizing how their interplay can catalyze simultaneous progress in science, art, and technology. These nexuses are not just points of intersection but are, in fact, crucibles of innovation and discovery. Through this interdisciplinary lens, we aim to deepen our understanding of the human experience, exploring how our perception shapes our reality and, in turn, how we express this reality through various forms of creativity. The *Emergent Nexuses* section, therefore, serves as a roadmap for future explorations of divergent perception in the broader context of computational neurophenomenology and digital arts.

Auditory pareidolia

In this thesis, I introduced a novel experimental framework for examining visual pareidolia, exploring its connections with trait creativity and specific neural patterns. Extending this research to auditory pareidolia presents a natural progression. A critical consideration in auditory pareidolia is defining what a 'meaningful auditory object' is. One way to address this challenge is by considering sense-making auditory experiences as being related to either the linguistic or the musical domains. Hence, linguistic auditory objects can be related to phonemes or words, whereas musical auditory objects could be linked to harmony (melodies, chords), rhythm, timbre, and sound source perception. In the context of linguistic ambiguity, techniques such as degrading word recordings or using electronic voice phenomena have been used to probe auditory pareidolia (Nees & Phillips, 2015; Williams et al., 2021). Extending the experimental design presented in this thesis, auditory fractal noise could be generated to explore the relation between stimulus fractal dimension and word illusions. The exploration of musical pareidolia is more

challenging due to the complex and dynamic nature of a 'musical object.' A promising initial step might entail evaluating the 'musicality' of ambiguous auditory stimuli on a spectrum or investigating the perceptual pitch of a melody within multistable sounds composed of complex harmonic frequencies, which could result in the formation of multiple potential virtual pitches. I further suggest that the Biotuner Toolbox could help to develop cognitive models of auditory perceptual binding that will allow to generate multistable stimuli.

Divergent perception in self-referential narratives

In advancing our understanding of pareidolia's relationship with creativity, a promising future direction involves exploring the originality of pareidolic percepts. By employing computational semantics, such as Latent Semantic Analysis (LSA), we can quantify the semantic distance between words used to describe these percepts. This method offers a novel way to link perceptual and semantic creativity. Pareidolia also offers a unique lens to investigate the origins of narratives. It's well-documented that artists often draw on pareidolic experiences to generate ideas for scenes, dialogues, and character interactions (da Vinci & McCurdy, 1958; Gamboni, 2002). Delving into how distinct and semantically varied pareidolic percepts shape narrative construction can offer insights into the cognitive foundations of innovative storytelling and narrative diversity. Tools like Divergent Semantic Integration (DSI) (Johnson et al., 2022), designed to measure the semantic divergence within a story's sentences, are particularly relevant in this context. Additionally, this line of inquiry could explore the role of visual stimuli properties, such as fractality, in the development of embodied narratives. Ultimately, this research could deepen our understanding of how perceptual experiences, in interaction with the properties of sensory information, inform and drive the formation of varied, self-referential narratives. Interestingly, a theory of narrative creativity has recently been proposed, stating that narrative techniques could foster shifts in perspectives and be used in creativity training (Fletcher & Benveniste, 2022).

Pareidolia in nature, human and machine

I propose that the phenomenon of pareidolia also offers promise in the comparison between human and machine perception. Indeed, both can be conceived as relying on generative processes (A. Clark, 2013; Wittrock, 1992; Xu et al., 2015) and generative models have already been used for the simulation of visual hallucinations (Rastelli et al., 2022; Zhang et al., 2017). Future works could delve into how pareidolia manifests in natural environments and how it is interpreted differently by humans and machines. In natural settings, pareidolia offers a window into the deep interplay between human cognition and the natural world. A logical next step would be to evaluate pareidolic patterns observed in natural images, such as cloud formations, rock structures, and foliage, as well as in AI generated images. This research would help to understand how humans derive meaning and form patterns from the randomness inherent in nature and how these interpretations align with or diverge from artificial intelligence's assessments. By employing advanced image recognition technologies, we can analyze both natural and algorithmically generated fractal images to discern patterns and shapes that elicit pareidolic responses. This comparison could shed light on perceptual differences between human and machine vision, as well as enhance our understanding of how AI algorithms can be improved to mimic human-like pattern recognition. Furthermore, this opens new avenues in the exploration of the cultural and psychological aspects of pareidolia, through the investigation of how the concepts and images identified in natural pareidolia resonate with the collective imagery and cultural archetypes of the people inhabiting these natural environments. This area of research could strengthen the intersection of psychology, anthropology, and environmental studies, offering insights into how our surroundings influence our collective subconscious and cultural narratives. The investigation into pareidolia across nature, human cognition, and machine perception holds, I posit, the potential to unravel complex layers of interaction between our environment, our minds, and the rapidly evolving field of artificial intelligence.

Doing neurosciences with music theory

The interdisciplinary fusion of neuroscience and music theory epitomizes the innovative spirit of this thesis, emphasizing their synergistic potential in enhancing our understanding of brain function and states of consciousness. The development of the *Biotuner Toolbox*, initially intended to explore the creation of bio-inspired musical structures, sparked the idea that computational models of harmonicity can be used to dissociate cognitive states. Preliminary analyses revealed that harmonicity metrics allow to distinguish between different sleep stages and wakefulness, adding information to classical PSD analyses (see **Fig. S6.1**). Another preliminary analysis significantly dissociates between DMT and placebo conditions using similar metrics (see **Fig. S6.2**). These findings warrant a systematic investigation into how these new metrics can effectively distinguish between different states of consciousness.

Harmonicity in biological resonance

Harmonicity metrics might prove useful in expanding our analysis techniques involved in the study of cross-frequency coupling and resonance in biological systems. The General Resonance Theory of Consciousness (Hunt et al., 2019) introduces a model where harmonicity and phase-coupling coalesce to form a simplistic yet profound understanding of resonance. This concept gains empirical support from preliminary results using Kuramoto models, as shown in **Figure S6.3.**, where the enhancement of harmonicity in oscillators leads to maximized system coupling. Such findings propel us to consider the joint analysis of different life forms, such as plants and animals, to explore the universality and diversity of biological resonance. Our exploration into harmonicity metrics sheds light on their potential utility in refining analytical techniques used in studying cross-frequency coupling and resonance in biological systems. As we edge closer to understanding these complex interactions, these metrics might reveal novel

insights into the fundamental principles governing neural communication and integrative processes.

Biofeedback as a technology of ambiguity: the uncanny valley of the projected self

Biofeedback mechanisms can be leveraged to create a bridge between the subjective inner world of human consciousness and the physical substrates of neural processes. This technology allows individuals to gain insights into their physiological states, which are typically unconscious. By translating biosignals, such as brainwaves, into auditory or visual outputs, biofeedback acts as a unique mirror, reflecting the intricate workings of the mind. This reflection can be both enlightening and unsettling, as individuals confront direct manifestations of their cognitive and emotional states. The concept of the "uncanny valley" (Mori et al., 2012) finds a novel interpretation in biofeedback. Here, the discomfort traditionally associated with near-human artificial entities in robotics is mirrored in the experience of individuals confronting intimate reflections of their inner states. This phenomenon underscores the fine line between self-perception and objective data, creating a dissonance as the line between self-perception and objective data becomes blurred. The biofeedback thus creates an "uncanny valley" of the self, where the familiarity of one's inner processes is juxtaposed with the strangeness of their external representation.

Biofeedback presents a unique method for amplifying pareidolia, a process where random or vague stimuli are perceived as significant or familiar. I suggest that by translating complex biosignals into sensory outputs, biofeedback engages individuals in a feedback loop that accentuates the tendency to find meaningful patterns in ambiguous inputs. This process does more than just deepen personal insights into creativity; it actively harnesses the inherent

ambiguities in biosignals to stimulate pareidolia. Consequently, this enhanced pareidolia could offer a richer understanding of individual interpretive skills and cognitive processes.

Simultaneously, biofeedback systems hold the potential to emulate altered states of consciousness by manipulating stimuli properties, leading to cyber-psychotropic states. These digitally-induced altered states, resembling the effects of psychoactive substances, can be reached through the strategic alteration of sensory inputs in a cybernetic environment (Suzuki et al., 2017). This manipulation relies on the creation of immersive experiences that mimic the cognitive and perceptual features of states such as deep meditation or psychedelic experiences. Since such states are often associated with heightened pareidolic experiences, I suggest that the ambiguity of generative sensory environments can emulate altered perceptual experience participating in the emergence of cyber-psychotropic states. Thus, I suggest that biofeedback emerges as a tool for introspection as well as a means to explore and expand the human experience of creativity and perception.

The integration of artificial intelligence in biofeedback systems (DiPaola & Song, 2023; Idrobo-Ávila et al., 2022; Kitson et al., 2019) offers a dual-faceted approach to enhancing human creativity and consciousness exploration. Firstly, by employing artificial neural networks to model various altered states of consciousness, these states can be transformed into specific neurofeedback targets. This novel approach allows for more precise guidance in directing the trajectory of mental states during neurofeedback sessions. By identifying and modeling the neural patterns associated with these altered states, such as deep meditation or heightened creativity, AI-driven neurofeedback can assist individuals in achieving these states more effectively and consistently. Secondly, the role of generative AI in biofeedback is to create customized content that aligns precisely with the desired neurofeedback goals. This involves using AI to analyze the individual's current neural state in real-time and adaptively generate stimuli—visual, auditory, or

sensory—that maximize the trajectory towards this state. The aim is to create an immersive experience that effectively guides the individual towards their targeted mental state.

Lastly, the merging of biofeedback with virtual and augmented reality technologies introduces the concept of neuro-enchantment and technological hypnosis. These technologies can induce states of enchantment or transformation, significantly influencing creativity and perception (Ali et al., 2014). By immersing individuals in artificially created environments that respond to their biosignals, these technologies can alter one's sense of reality, thereby opening new realms of creative expression and self-exploration. In conclusion, biofeedback stands at the forefront of exploring the intricate relationship between human perception, creativity, and technology. By enhancing pareidolia, emulating altered states, integrating generative AI, and utilizing advanced virtual technologies, biofeedback serves as a powerful tool for exploring the ambiguous territory of the projected self. It offers insights into the depths of human creativity, paving the way for new forms of artistic expression and collaborative creativity.

Conclusion

This thesis has explored how perceptual ambiguity participates in the creative process, proposing an experimental paradigm for the study of unconstrained pareidolia through the manipulation of statistical properties of visual stimuli. It was shown that pareidolia is linked to the capacity for divergent thinking and is underpinned by unique oscillatory patterns and scale-free/complexity dynamics in the brain. These findings mark the initial steps towards a systematic exploration of divergent perception. Furthermore, the significance of harmonicity in analyzing biosignals was highlighted, incorporating analytical techniques from music theory into cognitive neuroscience. Additionally, this work introduced a Python toolbox aimed at examining the harmonicity of biosignals. This toolbox serves both the scientific investigation of biological states and the innovative exploration of new musical forms.

References

- Abergel, D. (2019). Creative ambiguity. *Nature Physics*, 15(5), 421-421. <https://doi.org/10.1038/s41567-019-0518-4>
- Abraham, A. (2016). The imaginative mind. *Human Brain Mapping*, 37(11), 4197-4211. <https://doi.org/10.1002/hbm.23300>
- Acebrón, J. A., Bonilla, L. L., Vicente, C. J. P., Ritort, F., & Spigler, R. (2005). The Kuramoto model : A simple paradigm for synchronization phenomena. *Reviews of Modern Physics*, 77(1), 137-185. <https://doi.org/10.1103/RevModPhys.77.137>
- Ader, L. (2020). Introduction to Microtonal Music. *Music in Central and Eastern Europe: Historical Outlines and Current Practices*, 11-44.
- Adrian, E. D., & Matthews, B. H. C. (1934). The Berger Rhythm : Potential changes feom the occipital lobes in man. *Brain*, 57, 355-385.
- Ahmad, J., Ellis, C., Leech, R., Voytek, B., Garces, P., Jones, E., Buitelaar, J., Loth, E., Dos Santos, F. P., Amil, A. F., Verschure, P. F. M. J., Murphy, D., & McAlonan, G. (2022). From mechanisms to markers : Novel noninvasive EEG proxy markers of the neural excitation and inhibition system in humans. *Translational Psychiatry*, 12(1), 467. <https://doi.org/10.1038/s41398-022-02218-z>
- Akdeniz, G. (2020). Brain activity underlying face and face pareidolia processing : An ERP study. *Neurological Sciences*, 41. <https://doi.org/10.1007/s10072-019-04232-4>
- Akdeniz, G., Toker, S., & Atli, I. (2018). Neural mechanisms underlying visual pareidolia processing : An fMRI study. *Pakistan Journal of Medical Sciences*, 34(6), 1560-1566. <https://doi.org/10.12669/pjms.346.16140>
- Aks, D. J., & Sprott, J. C. (1996). Quantifying Aesthetic Preference for Chaotic Patterns. *Empirical Studies of the Arts*, 14(1), 1-16. <https://doi.org/10.2190/6v31-7m9r-t9l5-cdg9>

- Alexander, V. N. (2013). Creativity : Self-Referential Mistaking, Not Negating. *Biosemiotics*, 6(2), 253-272. <https://doi.org/10.1007/s12304-012-9158-0>
- Ali, S. S., Lifshitz, M., & Raz, A. (2014). Empirical neuroenchantment : From reading minds to thinking critically. *Frontiers in Human Neuroscience*, 8. <https://doi.org/10.3389/fnhum.2014.00357>
- Almeida, L. S., Prieto, L. P., Ferrando, M., Oliveira, E., & Ferrándiz, C. (2008). Torrance Test of Creative Thinking : The question of its construct validity. *Thinking Skills and Creativity*, 3(1), 53-58. <https://doi.org/10.1016/j.tsc.2008.03.003>
- Amendt-Lyon, N. (2001). Art and Creativity in Gestalt Therapy. *Gestalt Review*, 5(4), 225-248. <https://doi.org/10.5325/gestaltreview.5.4.0225>
- Ashton, M. A., & McDonald, R. D. (1985). Effects of Hypnosis on Verbal and Non-Verbal Creativity. *International Journal of Clinical and Experimental Hypnosis*, 33(1), 15-26. <https://doi.org/10.1080/00207148508406632>
- Atasoy, S., Deco, G., Kringelbach, M. L., & Pearson, J. (2018). Harmonic Brain Modes : A Unifying Framework for Linking Space and Time in Brain Dynamics. *Neuroscientist*, 24(3), 277-293. <https://doi.org/10.1177/1073858417728032>
- Atasoy, S., Roseman, L., Kaelen, M., Kringelbach, M. L., Deco, G., & Carhart-Harris, R. L. (2017). Connectome-harmonic decomposition of human brain activity reveals dynamical repertoire re-organization under LSD. *Scientific Reports*, 7(1). <https://doi.org/10.1038/s41598-017-17546-0>
- Atasoy, S., Vohryzek, J., Deco, G., Carhart-Harris, R. L., & Kringelbach, M. L. (2018). Common neural signatures of psychedelics : Frequency-specific energy changes and repertoire expansion revealed using connectome-harmonic decomposition. In *Progress in Brain Research* (Vol. 242, p. 97-120). Elsevier. <https://doi.org/10.1016/bs.pbr.2018.08.009>

- Baber, C., Chemero, T., & Hall, J. (2019). What the Jeweller's Hand Tells the Jeweller's Brain : Tool Use, Creativity and Embodied Cognition. *Philosophy & Technology*, 32(2), 283-302.
<https://doi.org/10.1007/s13347-017-0292-0>
- Bagdasaryan, J., & Quyen, M. L. V. (2013). Experiencing your brain : Neurofeedback as a new bridge between neuroscience and phenomenology. *Frontiers in Human Neuroscience*, 7(OCT), 1-10.
<https://doi.org/10.3389/fnhum.2013.00680>
- Baggott, M. J. (2015). *Psychedelics and creativity : A review of the quantitative literature* [Preprint]. PeerJ PrePrints. <https://doi.org/10.7287/peerj.preprints.1202v1>
- Baltus, A., & Herrmann, C. S. (2016). The importance of individual frequencies of endogenous brain oscillations for auditory cognition – A short review. *Brain Research*, 1640, 243-250.
<https://doi.org/10.1016/j.brainres.2015.09.030>
- Barbot, B., Besançon, M., & Lubart, T. (2015). Creative potential in educational settings : Its nature, measure, and nurture Baptiste. *International Journal of Primary, Elementary and Early Years Education ISSN:*, 3-13, 371-381. <https://doi.org/10.1080/03004279.2015.1020643>
- Barbour, B. J. M. (1947). Bach and « The Art of Temperament ». *The musical quaterly*, 33(1), 64-89.
- Barik, K., Jones, R., Bhattacharya, J., & Saha, G. (2019). Investigating the Influence of Prior Expectation in Face Pareidolia using Spatial Pattern. In M. Tanveer & R. B. Pachori (Éds.), *Machine Intelligence and Signal Analysis* (Vol. 748, p. 437-451). Springer Singapore. https://doi.org/10.1007/978-981-13-0923-6_38
- Barr, D. J. (2013). Random effects structure for testing interactions in linear mixed-effects models. *Frontiers in Psychology*, 4(June), 3-4. <https://doi.org/10.3389/fpsyg.2013.00328>
- Barrett, J. L. (2000). Exploring the natural foundations of religion. *Religion and Cognition: A Reader*, 4(1), 86-98.

- Bartsch, R., Kantelhardt, J. W., Penzel, T., & Havlin, S. (2007). Experimental evidence for phase synchronization transitions in human cardio-respiratory system. *Physical Review Letters*, *98*(5), 054102. <https://doi.org/10.1103/PhysRevLett.98.054102>
- Bates, D., Mächler, M., Bolker, B. M., & Walker, S. C. (2015a). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). <https://doi.org/10.18637/jss.v067.i01>
- Bates, D., Mächler, M., Bolker, B. M., & Walker, S. C. (2015b). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*(1). <https://doi.org/10.18637/jss.v067.i01>
- Batey, M., & Furnham, A. (2008). The relationship between measures of creativity and schizotypy. *Personality and Individual Differences*, *45*(8), 816-821. <https://doi.org/10.1016/j.paid.2008.08.014>
- Beaty, R. E., Benedek, M., Barry Kaufman, S., & Silvia, P. J. (2015). Default and Executive Network Coupling Supports Creative Idea Production. *Scientific Reports*, *5*(1), 10964. <https://doi.org/10.1038/srep10964>
- Beaty, R. E., Benedek, M., Silvia, P. J., & Schacter, D. L. (2016). Creative Cognition and Brain Network Dynamics. *Trends in Cognitive Sciences*, *20*(2), 87-95. <https://doi.org/10.1016/j.tics.2015.10.004>
- Beaty, R. E., Chen, Q., Christensen, A. P., Qiu, J., Silvia, P. J., & Schacter, D. L. (2018). Brain networks of the imaginative mind : Dynamic functional connectivity of default and cognitive control networks relates to openness to experience. *Human Brain Mapping*, *39*(2), 811-821. <https://doi.org/10.1002/hbm.23884>
- Beghetto, R. A. (2019). Structured Uncertainty : How Creativity Thrives Under Constraints and Uncertainty. In C. A. Mullen (Éd.), *Creativity Under Duress in Education?* (Vol. 3, p. 27-40). Springer International Publishing. https://doi.org/10.1007/978-3-319-90272-2_2

- Beghetto, R. A., & Jaeger, G. J. (2022). Uncertainty : A Catalyst for Creativity, Learning and Development. Creativity Theory and Action in Education. Volume 6. In *Creativity Theory and Action in Education*. Springer. <https://doi.org/10.1007/978-3-030-98729-9>
- Belayachi, S., Laloyaux, J., Larøi, F., & Van der Linden, M. (2015). Internal Encoding Style and Schizotypy : Toward a Conceptually Driven Account of Positive Symptoms. *Journal of Personality Disorders*, 29(3), 303-315. https://doi.org/10.1521/pedi_2014_28_157
- Bell, S., & Gabora, L. (2016). A Music-generating System Based on Network Theory Honing Theory : Creativity as a Complex Self-Organization Edge of Chaos. *Proceedings of the 7th International Conference on Computational Creativity, June*, 299-306.
- Bellemare-Pepin, A., Harel, Y., O'Byrne, J., Mageau, G., Dietrich, A., & Jerbi, K. (2022). Processing visual ambiguity in fractal patterns : Pareidolia as a sign of creativity. *iScience*, 25(10), 105103. <https://doi.org/10.1016/j.isci.2022.105103>
- Benedek, M., Bergner, S., Könen, T., Fink, A., & Neubauer, A. C. (2011). EEG alpha synchronization is related to top-down processing in convergent and divergent thinking. *Neuropsychologia*, 49(12), 3505-3511. <https://doi.org/10.1016/j.neuropsychologia.2011.09.004>
- Benedek, M., Franz, F., Heene, M., & Neubauer, A. C. (2012). Differential effects of cognitive inhibition and intelligence on creativity. *Personality and Individual Differences*, 53(4), 480-485. <https://doi.org/10.1016/j.paid.2012.04.014>
- Benetos, E., & Holzapfel, A. (2015). Automatic transcription of Turkish microtonal music. *The Journal of the Acoustical Society of America*, 138(4), 2118-2130. <https://doi.org/10.1121/1.4930187>
- Berger. (1929). *Über das Elektrenkephalogramm des Menschen*.
- Berger, C. C., & Ehrsson, H. H. (2014). The Fusion of Mental Imagery and Sensation in the Temporal Association Cortex. *The Journal of Neuroscience*, 34(41), 13684-13692. <https://doi.org/10.1523/JNEUROSCI.0943-14.2014>

- Bergum, J. E., & Bergum, B. O. (1979). Self-perceived creativity and ambiguous figure reversal rates. *Bulletin of the Psychonomic Society*, 14(5), 373-374. <https://doi.org/10.3758/BF03329483>
- Berkovich-Ohana, A., & Glicksohn, J. (2014). The consciousness state space (CSS)-a unifying model for consciousness and self. *Frontiers in Psychology*, 5(APR), 1-19. <https://doi.org/10.3389/fpsyg.2014.00341>
- Bidelman, G. M., & Krishnan, A. (2009). Neural correlates of consonance, dissonance, and the hierarchy of musical pitch in the human brainstem. *Journal of Neuroscience*, 29(42), 13165-13171. <https://doi.org/10.1523/JNEUROSCI.3900-09.2009>
- Bies, A., Boydston, C., Taylor, R., & Sereno, M. (2016). Relationship between Fractal Dimension and Spectral Scaling Decay Rate in Computer-Generated Fractals. *Symmetry*, 8(7), 66. <https://doi.org/10.3390/sym8070066>
- Bies, A. J., Blanc-Goldhammer, D. R., Boydston, C. R., Taylor, R. P., & Sereno, M. E. (2016). Aesthetic Responses to Exact Fractals Driven by Physical Complexity. *Frontiers in Human Neuroscience*, 10. <https://doi.org/10.3389/fnhum.2016.00210>
- Bies, A., Kikumoto, A., Boydston, C., Greenfield, A., Chauvin, K., Taylor, R., & Sereno, M. (2016). Percepts from noise patterns : The role of fractal dimension in object pareidolia. *Journal of Vision*, 16(12), 790. <https://doi.org/10.1167/16.12.790>
- Bilder, R. M., & Knudsen, K. S. (2014). Creative cognition and systems biology on the edge of chaos. *Frontiers in Psychology*, 5. <https://doi.org/10.3389/fpsyg.2014.01104>
- Blake, A., & Palmisano, S. (2021). Divergent Thinking Influences the Perception of Ambiguous Visual Illusions. *Perception*, 50(5), 418-437. <https://doi.org/10.1177/03010066211000192>
- Bogdanov, D., Wack, N., Gómez Gutiérrez, E., Gulati, S., Herrera Boyer, P., Mayor, O., Roma Trepát, G., Salamon, J., Zapata González, J. R., & Serra, X. (2013). *Essentia : An audio analysis library for music information retrieval*. <http://repositori.upf.edu/handle/10230/32252>

- Bones, O., Hopkins, K., Krishnan, A., & Plack, C. J. (2014). Phase locked neural activity in the human brainstem predicts preference for musical consonance. *Neuropsychologia*, *58*(1), 23-32.
<https://doi.org/10.1016/j.neuropsychologia.2014.03.011>
- Boomsalter, P., & Creel, W. (1961). The Long Pattern Hypothesis in Harmony and Hearing. *Journal of Music Theory*, *5*(1), 2-31.
- Boonstra, T. W., He, B. J., & Daffertshofer, A. (2013). Scale-free dynamics and critical phenomena in cortical activity. *Frontiers in Physiology*, *4*. <https://doi.org/10.3389/fphys.2013.00079>
- Bouchaud, J.-P., Potters, M., & Meyer, M. (2000). Apparent multifractality in financial time series. *The European Physical Journal B*, *16*(3), 569-571. <https://doi.org/10.1007/s100510050073>
- Bowers, P. (1978). Hypnotizability, Creativity and the Role of Effortless Experiencing. *International Journal of Clinical and Experimental Hypnosis*, *26*(3), 184-202.
<https://doi.org/10.1080/00207147808409320>
- Bown, O. (2009). A framework for ecosystem-based generative music. *Proceedings of the 6th Sound and Music Computing Conference, SMC 2009, July*, 195-200.
- Brattico, E., & Pearce, M. (2013). The neuroaesthetics of music. *Psychology of Aesthetics, Creativity, and the Arts*, *7*(1), 48-61. <https://doi.org/10.1037/a0031624>
- Bridges, B. (2012). *Towards a Perceptually-grounded Theory of Microtonality : Issues in sonority, scale construction and auditory perception and cognition*.
- Brugger, P. (2001). *From Haunted Brain To Haunted Science*.
- Burch, G. S. J., Pavelis, C., Hemsley, D. R., & Corr, P. J. (2006). Schizotypy and creativity in visual artists. *British Journal of Psychology*, *97*(2), 177-190. <https://doi.org/10.1348/000712605X60030>
- Burt, W. (2023). *A new ecosystem for microtonal computer music exploration and composition*.

- Camarda, A., Borst, G., Agogu , M., Habib, M., Weil, B., Houd , O., & Cassotti, M. (2018). Do we need inhibitory control to be creative? Evidence from a dual-task paradigm. *Psychology of Aesthetics, Creativity, and the Arts*, 12(3), 351-358. <https://doi.org/10.1037/aca0000140>
- Campo, A. de. (2007). TOWARD A DATA SONIFICATION DESIGN SPACE MAP. *Proceedings of the 13th International Conference on Auditory Display Montr al Canada*, 342-347.
- Carhart-Harris, R. L. (2018a). The entropic brain—Revisited. *Neuropharmacology*, 142, 167-178. <https://doi.org/10.1016/j.neuropharm.2018.03.010>
- Carhart-Harris, R. L. (2018b). The entropic brain—Revisited. *Neuropharmacology*. <https://doi.org/10.1016/j.neuropharm.2018.03.010>
- Carhart-Harris, R. L., & Friston, K. J. (2019). REBUS and the Anarchic Brain : Toward a Unified Model of the Brain Action of Psychedelics. *Pharmacological Reviews*, 71(3), 316-344. <https://doi.org/10.1124/pr.118.017160>
- Carhart-Harris, R. L., Leech, R., Hellyer, P. J., Shanahan, M., Feilding, A., Tagliazucchi, E., Chialvo, D. R., & Nutt, D. (2014). The entropic brain : A theory of conscious states informed by neuroimaging research with psychedelic drugs. *Frontiers in Human Neuroscience*, 8. <https://doi.org/10.3389/fnhum.2014.00020>
- Carlqvist, H., Nikulin, V. V., Str mberg, J. O., & Brismar, T. (2005). Amplitude and phase relationship between alpha and beta oscillations in the human electroencephalogram. *Medical and Biological Engineering and Computing*, 43(5), 599-607. <https://doi.org/10.1007/BF02351033>
- Carpentier, S. (2020). Complexity matching : Brain signals mirror environment information patterns during music listening and reward. *Journal of Cognitive Neuroscience*, 32(4), 734-745.
- Carson, S. H. (2011). Creativity and Psychopathology : A Shared Vulnerability Model. *The Canadian Journal of Psychiatry*, 56(3), 144-153. <https://doi.org/10.1177/070674371105600304>

- Carson, S. H., Peterson, J. B., & Higgins, D. M. (2003). Decreased Latent Inhibition Is Associated With Increased Creative Achievement in High-Functioning Individuals. *Journal of Personality and Social Psychology, 85*(3), 499-506. <https://doi.org/10.1037/0022-3514.85.3.499>
- Cartwright, J. H. E., González, D. L., & Piro, O. (2021). Dynamical systems, celestial mechanics, and music : Pythagoras revisited. *The Mathematical Intelligencer, 43*(1), 25-39. <https://doi.org/10.1007/s00283-020-10025-x>
- Castelhano, J., Rebola, J., Leitão, B., Rodriguez, E., & Castelo-Branco, M. (2013). To Perceive or Not Perceive : The Role of Gamma-band Activity in Signaling Object Percepts. *PLoS ONE, 8*(6), e66363. <https://doi.org/10.1371/journal.pone.0066363>
- Cavanagh, J. F., Figueroa, C. M., Cohen, M. X., & Frank, M. J. (2012). Frontal Theta Reflects Uncertainty and Unexpectedness during Exploration and Exploitation. *Cerebral Cortex, 22*(11), 2575-2586. <https://doi.org/10.1093/cercor/bhr332>
- Cavanagh, J. F., & Frank, M. J. (2014). Frontal theta as a mechanism for cognitive control. *Trends in Cognitive Sciences, 18*(8), 414-421. <https://doi.org/10.1016/j.tics.2014.04.012>
- Chan, P. Y., Dong, M., & Li, H. (2019a). The Science of Harmony : A Psychophysical Basis for Perceptual Tensions and Resolutions in Music. *Research, 2019*, 1-22. <https://doi.org/10.34133/2019/2369041>
- Chan, P. Y., Dong, M., & Li, H. (2019b). The Science of Harmony : A Psychophysical Basis for Perceptual Tensions and Resolutions in Music. *Research, 2019*, 2019/2369041. <https://doi.org/10.34133/2019/2369041>
- Chatterjee, A. (2014). *The Aesthetic Brain : How We Evolved to Desire Beauty and Enjoy Art*. OUP USA.
- Chen, R., Xiong, Y., Zhuge, S., Li, Z., Chen, Q., He, Z., Wu, D., Hou, F., & Zhou, J. (2023). Regulation and prediction of multistable perception alternation. *Chaos, Solitons & Fractals, 172*, 113564. <https://doi.org/10.1016/j.chaos.2023.113564>

- Chiarion, G., Sparacino, L., Antonacci, Y., Faes, L., & Mesin, L. (2023). Connectivity Analysis in EEG Data : A Tutorial Review of the State of the Art and Emerging Trends. *Bioengineering*, *10*(3), Article 3. <https://doi.org/10.3390/bioengineering10030372>
- Chirila, C., & Feldman, A. (2012). Study of latent inhibition at high-level creative personality The link between creativity and psychopathology. *Procedia - Social and Behavioral Sciences*, *33*, 353-357. <https://doi.org/10.1016/j.sbspro.2012.01.142>
- Chiu, I., & Shu, L. H. (2012). Investigating effects of oppositely related semantic stimuli on design concept creativity. *Journal of Engineering Design*, *23*(4), 271-296. <https://doi.org/10.1080/09544828.2011.603298>
- Chrysikou, E. G. (2019). Creativity in and out of (cognitive) control. *Current Opinion in Behavioral Sciences*, *27*, 94-99. <https://doi.org/10.1016/j.cobeha.2018.09.014>
- Ciesielski, T. H., Aldrich, M. C., Marsit, C. J., Hiatt, R. A., & Williams, S. M. (2017). Transdisciplinary approaches enhance the production of translational knowledge. *Translational Research*, *182*, 123-134. <https://doi.org/10.1016/j.trsl.2016.11.002>
- Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of cognitive science. *Behavioral and Brain Sciences*, *36*(3), 181-204. <https://doi.org/10.1017/S0140525X12000477>
- Clark, T. S., & Linzer, D. A. (2015). Should I Use Fixed or Random Effects? *Political Science Research and Methods*, *3*(2), 399-408. <https://doi.org/10.1017/psrm.2014.32>
- Cohen, M. X. (2017). Where Does EEG Come From and What Does It Mean? *Trends in Neurosciences*, *40*(4), 208-218. <https://doi.org/10.1016/j.tins.2017.02.004>
- Cohen, M. X., Elger, C. E., & Fell, J. (2009). Oscillatory Activity and Phase–Amplitude Coupling in the Human Medial Frontal Cortex during Decision Making. *Journal of Cognitive Neuroscience*, *21*(2), 390-402. <https://doi.org/10.1162/jocn.2008.21020>

- Colombetti, G. (2013). Enaction, Sense-Making, and Emotion. *Enaction*, April, 144-164.
<https://doi.org/10.7551/mitpress/9780262014601.003.0006>
- Costa, M. Â. (2023). A Dose of Creativity : An Integrative Review of the Effects of Serotonergic Psychedelics on Creativity. *Journal of Psychoactive Drugs*, 55(3), 299-309.
<https://doi.org/10.1080/02791072.2022.2106805>
- Creswell, J. D., Bursley, J. K., & Satpute, A. B. (2013). Neural reactivation links unconscious thought to decision-making performance. *Social Cognitive and Affective Neuroscience*, 8(8), 863-869.
<https://doi.org/10.1093/scan/nst004>
- Csizmadia, P., Nagy, B., Czigler, I., & Gaál, Z. A. (2022). The effect of ambiguous and unambiguous stimuli on target processing in less creative and more creative groups. *Neuropsychologia*, 175, 108355.
<https://doi.org/10.1016/j.neuropsychologia.2022.108355>
- Cutting, J. E., & Garvin, J. J. (1987a). Fractal curves and complexity. *Perception & Psychophysics*, 42(4), 365-370. <https://doi.org/10.3758/BF03203093>
- Cutting, J. E., & Garvin, J. J. (1987b). Fractal curves and complexity. *Perception & Psychophysics*, 42(4), 365-370. <https://doi.org/10.3758/BF03203093>
- Dahlstedt, P. (2009). Thoughts on creative evolution : A meta-generative approach to composition. *Contemporary Music Review*, 28(1), 43-55. <https://doi.org/10.1080/07494460802664023>
- Dailey, A., Martindale, C., & Borkum, J. (1997). Creativity, Synesthesia, and Physiognomic Perception. *Creativity Research Journal*, 10(1), 1-8. https://doi.org/10.1207/s15326934crj1001_1
- D'Angelo, D. (2019). The phenomenology of embodied attention. *Phenomenology and the Cognitive Sciences*. <https://doi.org/10.1007/s11097-019-09637-2>
- D'Angelo, D. (2020). The phenomenology of embodied attention. *Phenomenology and the Cognitive Sciences*, 19(5), 961-978. <https://doi.org/10.1007/s11097-019-09637-2>

- da Vinci, L., & McCurdy, E. (1958). The notebooks of Leonardo da Vinci. (*No Title*).
<https://cir.nii.ac.jp/crid/1130282271689497600>
- Davy, M., & Godsill, S. J. (2003). *Bayesian harmonic models for musical pitch estimation and analysis*.
December, II-II. <https://doi.org/10.1109/icassp.2002.1006106>
- D’Croz-Baron, D. F., Bréchet, L., Baker, M., & Karp, T. (2021). Auditory and Visual Tasks Influence the
Temporal Dynamics of EEG Microstates During Post-encoding Rest. *Brain Topography*, *34*(1),
19-28. <https://doi.org/10.1007/s10548-020-00802-4>
- De Pisapia, N., Bacci, F., Parrott, D., & Melcher, D. (2016). Brain networks for visual creativity : A
functional connectivity study of planning a visual artwork. *Scientific Reports*, *6*(1), 39185.
<https://doi.org/10.1038/srep39185>
- de Arcangelis, L., Perrone-Capano, C., & Herrmann, H. J. (2006). Self-Organized Criticality Model for
Brain Plasticity. *Physical Review Letters*, *96*(2), 028107.
<https://doi.org/10.1103/PhysRevLett.96.028107>
- de Dreu, C. K. W., Nijstad, B. A., & Baas, M. (2011). Behavioral activation links to creativity because of
increased cognitive flexibility. *Social Psychological and Personality Science*, *2*(1), 72-80.
<https://doi.org/10.1177/1948550610381789>
- Del Bianco, T., Haartsen, R., Mason, L., Carter Leno, V. M., Springer, P., Potter, M., Mackay, W., Smit, P.,
Du Plessis, C., Brink, L., Johnson, M. H., Murphy, D., Loth, E., Odendaal, H., & Jones, E. J. H.
(2023). *The importance of decomposing periodic and aperiodic EEG signals for assessment of
brain function in a global context* [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/ctbjw>
- Deppman, A., & Andrade-II, E. O. (2021). *Flux of information in scale-free networks*.
- Depraz, N., & Desmidt, T. (2019). Cardiophenomenology : A refinement of neurophenomenology.
Phenomenology and the Cognitive Sciences, *18*, 493-507. <https://doi.org/10.1007/s11097-018-9590-y>

- Deutsch, D. (1991). The Tritone Paradox : An Influence of Language on Music Perception. *Music Perception, 8*(4), 335-347. <https://doi.org/10.2307/40285517>
- Deza, M. M., & Deza, E. (2014). Image and Audio Distances. In M. M. Deza & E. Deza (Éds.), *Encyclopedia of Distances* (p. 387-411). Springer. https://doi.org/10.1007/978-3-662-44342-2_21
- Diana, L., Frei, M., Chesham, A., de Jong, D., Chiffi, K., Nyffeler, T., Bassetti, C. L., Goebel, N., Eberhard-Moscicka, A. K., & Müri, R. M. (2021). A divergent approach to pareidolias—Exploring creativity in a novel way. *Psychology of Aesthetics, Creativity, and the Arts, 15*(2), 313-323. <https://doi.org/10.1037/aca0000293>
- Dietrich, A. (2004). The cognitive neuroscience of creativity. *Psychonomic Bulletin & Review, 11*(6), 1011-1026. <https://doi.org/10.3758/BF03196731>
- Dietrich, A. (2007). Who's afraid of a cognitive neuroscience of creativity? *Methods, 42*(1), 22-27. <https://doi.org/10.1016/j.ymeth.2006.12.009>
- Dietrich, A. (2018). Types of creativity. *Psychonomic Bulletin and Review*. <https://doi.org/10.3758/s13423-018-1517-7>
- Dietrich, A. (2019a). Types of creativity. *Psychonomic Bulletin & Review, 26*(1), 1-12. <https://doi.org/10.3758/s13423-018-1517-7>
- Dietrich, A. (2019b). Where in the brain is creativity : A brief account of a wild-goose chase. *Current Opinion in Behavioral Sciences, 27*, 36-39. <https://doi.org/10.1016/j.cobeha.2018.09.001>
- Dietrich, A., & Haider, H. (2015). Human creativity, evolutionary algorithms, and predictive representations : The mechanics of thought trials. *Psychonomic Bulletin & Review, 22*(4), 897-915. <https://doi.org/10.3758/s13423-014-0743-x>
- Dietrich, A., & Kanso, R. (2010). A review of EEG, ERP, and neuroimaging studies of creativity and insight. *Psychological Bulletin, 136*(5), 822-848. <https://doi.org/10.1037/a0019749>

- Dijksterhuis, A., & Nordgren, L. F. (2006). A Theory of Unconscious Thought. *Perspectives on Psychological Science*, 1(2).
- Dijkstra, N., & Fleming, S. M. (2023). Subjective signal strength distinguishes reality from imagination. *Nature Communications*, 14(1), 1627. <https://doi.org/10.1038/s41467-023-37322-1>
- Dimkov, P. R. (2018). The Genius of Creativity and the Creativity of Genius : The Neuro-Dynamics of Creativity in Karl Jaspers and Sigmund Freud. *Journal of Genius and Eminence*, 3(Fall 2018), 83-92. <https://doi.org/10.18536/jge.2018.04.3.1.07>
- Ding, S., Meng, L., Han, Y., & Xue, Y. (2017). A Review on Feature Binding Theory and Its Functions Observed in Perceptual Process. *Cognitive Computation*, 9(2), 194-206. <https://doi.org/10.1007/s12559-016-9446-0>
- DiPaola, S., & Gabora, L. (2009). Incorporating characteristics of human creativity into an evolutionary art algorithm. *Genetic Programming and Evolvable Machines*, 10(2), 97-110. <https://doi.org/10.1007/s10710-008-9074-x>
- DiPaola, S., & Song, M. (2023). Combining Artificial Intelligence, Bio-Sensing and Multimodal Control for Bio-Responsive Interactives. *Companion Publication of the 25th International Conference on Multimodal Interaction*, 318-322. <https://doi.org/10.1145/3610661.3616183>
- Donoghue, T., Haller, M., Peterson, E. J., Varma, P., Sebastian, P., Gao, R., Noto, T., Lara, A. H., Wallis, J. D., Knight, R. T., Shestyuk, A., & Voytek, B. (2020). Parameterizing neural power spectra into periodic and aperiodic components. *Nature Neuroscience*, 23(12), Article 12. <https://doi.org/10.1038/s41593-020-00744-x>
- Dorfman, L., Martindale, C., Gassimova, V., & Vartanian, O. (2008). Creativity and speed of information processing : A double dissociation involving elementary versus inhibitory cognitive tasks. *Personality and Individual Differences*, 44(6), 1382-1390. <https://doi.org/10.1016/j.paid.2007.12.006>

- Dorjee, D. (2016). Defining contemplative science : The metacognitive self-regulatory capacity of the mind, context of meditation practice and modes of existential awareness. *Frontiers in Psychology, 7*(NOV), 1-15. <https://doi.org/10.3389/fpsyg.2016.01788>
- Duan, Z., Zhang, Y., Zhang, C., & Shi, Z. (2008). Unsupervised single-channel music source separation by average harmonic structure modeling. *IEEE Transactions on Audio, Speech and Language Processing, 16*(4), 766-778. <https://doi.org/10.1109/TASL.2008.919073>
- Dubois, C., & Davy, M. (2007). Joint detection and tracking of time-varying harmonic components : A flexible bayesian approach. *IEEE Transactions on Audio, Speech and Language Processing, 15*(4), 1283-1295. <https://doi.org/10.1109/TASL.2007.894522>
- Ehm, W., Bach, M., & Kornmeier, J. (2011). Ambiguous figures and binding : EEG frequency modulations during multistable perception: Ambiguous figures and binding. *Psychophysiology, 48*(4), 547-558. <https://doi.org/10.1111/j.1469-8986.2010.01087.x>
- Ellamil, M., Dobson, C., Beeman, M., & Christoff, K. (2012). Evaluative and generative modes of thought during the creative process. *NeuroImage, 59*(2), 1783-1794. <https://doi.org/10.1016/j.neuroimage.2011.08.008>
- Ergenoglu, T., Demiralp, T., Bayraktaroglu, Z., Ergen, M., Beydagi, H., & Uresin, Y. (2004). Alpha rhythm of the EEG modulates visual detection performance in humans. *Cognitive Brain Research, 20*(3), 376-383. <https://doi.org/10.1016/j.cogbrainres.2004.03.009>
- Erkut, C. (2004). *BIOACOUSTIC MODELING FOR SOUND SYNTHESIS: A CASE STUDY OF ODONTOCETI CLICKS*.
- Eslahi, S. V., Dabanloo, N. J., & Maghooli, K. (2019). A GA-based feature selection of the EEG signals by classification evaluation : Application in BCI systems (arXiv:1903.02081). arXiv. <http://arxiv.org/abs/1903.02081>

Euler, L. (1739). *Tentamen nouæ theoriæ musicæ ex certissimis harmoniæ principiis dilucide expositæ*.
Auctore Leonardo Eulero. ex typographia Academiæ Scientiarum.

Faini, A., Parati, G., & Castiglioni, P. (2021). Multiscale assessment of the degree of multifractality for physiological time series. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 379(2212), 20200254.

<https://doi.org/10.1098/rsta.2020.0254>

Farkas, D., Denham, S. L., Bendixen, A., Tóth, D., Kondo, H. M., & Winkler, I. (2016). Auditory Multi-Stability : Idiosyncratic Perceptual Switching Patterns, Executive Functions and Personality Traits. *PLOS ONE*, 11(5), e0154810. <https://doi.org/10.1371/journal.pone.0154810>

Farnell, A. (2010). *Designing sound*. MIT Press.

Farnes, N., Juel, B. E., Nilsen, A. S., Romundstad, L. G., & Storm, J. F. (2020). Increased signal diversity/complexity of spontaneous EEG, but not evoked EEG responses, in ketamine-induced psychedelic state in humans. *PLOS ONE*, 15(11), e0242056.

<https://doi.org/10.1371/journal.pone.0242056>

Fauvel, J., Flood, R., & Wilson, R. J. (Éds.). (2003). *Music and mathematics : From Pythagoras to fractals*. Oxford University Press.

Ferguson, K. (2011). *The Music of Pythagoras : How an Ancient Brotherhood Cracked the Code of the Universe and Lit the Path from Antiquity to Oute*. Bloomsbury Publishing USA.

Fink, A., Weber, B., Koschutnig, K., Benedek, M., Reishofer, G., Ebner, F., Papousek, I., & Weiss, E. M. (2014). Creativity and schizotypy from the neuroscience perspective. *Cognitive, Affective, & Behavioral Neuroscience*, 14(1), 378-387. <https://doi.org/10.3758/s13415-013-0210-6>

Fischer, R., & Landon, G. M. (1972). *On the Arousal State-Dependent Recall of 'Subconscious' Experience : Stateboundness*.

- Fischer, R., & Scheib, J. (1971). Creative performance and the hallucinogenic drug-induced creative experience or one man's brain-damage is another's creativity. *Confinia Psychiatrica*, *14*(3-4), 174-202.
- Fishman, Y. I., Volkov, I. O., Noh, M. D., Garell, P. C., Bakken, H., Arezzo, J. C., Howard, M. A., & Steinschneider, M. (2001). Consonance and dissonance of musical chords : Neural correlates in auditory cortex of monkeys and humans. *Journal of Neurophysiology*, *86*(6), 2761-2788.
<https://doi.org/10.1152/jn.2001.86.6.2761>
- Fletcher, A., & Benveniste, M. (2022). A new method for training creativity : Narrative as an alternative to divergent thinking. *Annals of the New York Academy of Sciences*, *1512*(1), 29-45.
<https://doi.org/10.1111/nyas.14763>
- Flowers, J. H., & Garbin, C. P. (1989). Creativity and Perception. In J. A. Glover, R. R. Ronning, & C. R. Reynolds (Éds.), *Handbook of Creativity* (p. 147-162). Springer US. https://doi.org/10.1007/978-1-4757-5356-1_8
- Fox, K. C. R., & Christoff, K. (2018). *The Oxford Handbook of Spontaneous Thought : Mind-wandering, Creativity, and Dreaming*. Oxford University Press.
- Fox, K. C. R., Spreng, R. N., Ellamil, M., Andrews-Hanna, J. R., & Christoff, K. (2015). The wandering brain : Meta-analysis of functional neuroimaging studies of mind-wandering and related spontaneous thought processes. *NeuroImage*, *111*, 611-621.
<https://doi.org/10.1016/j.neuroimage.2015.02.039>
- Fox, M. D., Snyder, A. Z., Vincent, J. L., & Raichle, M. E. (2007). Intrinsic Fluctuations within Cortical Systems Account for Intertrial Variability in Human Behavior. *Neuron*, *56*(1), 171-184.
<https://doi.org/10.1016/j.neuron.2007.08.023>
- Friederici, A. D. (2011). The Brain Basis of Language Processing : From Structure to Function. *Physiological Reviews*, *91*(4), 1357-1392. <https://doi.org/10.1152/physrev.00006.2011>

- Fries, P. (2009). Neuronal Gamma-Band Synchronization as a Fundamental Process in Cortical Computation. *Annual Review of Neuroscience*, 32(1), 209-224.
<https://doi.org/10.1146/annurev.neuro.051508.135603>
- Friston, K. (2005). A theory of cortical responses. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 360(1456), 815-836. <https://doi.org/10.1098/rstb.2005.1622>
- Fritz, T., Jentschke, S., Gosselin, N., Sammler, D., Peretz, I., Turner, R., Friederici, A. D., & Koelsch, S. (2009). Universal Recognition of Three Basic Emotions in Music. *Current Biology*, 19(7), 573-576.
<https://doi.org/10.1016/j.cub.2009.02.058>
- Fryer, M. (2012). Some Key Issues in Creativity Research and Evaluation as Seen From a Psychological Perspective. *Creativity Research Journal*, 24(1), 21-28.
<https://doi.org/10.1080/10400419.2012.649236>
- Fyfe, S., Williams, C., Mason, O., & Pickup, G. (2008). Apophenia, theory of mind and schizotypy : Perceiving meaning and intentionality in randomness. *Cortex*, 44(10), 1316-1325.
<https://doi.org/10.1016/j.cortex.2007.07.009>
- Gabora, L. (2016). A Possible Role for Entropy in Creative Cognition. *Proceedings of 3rd International Electronic and Flipped Conference on Entropy and Its Applications*, E001.
<https://doi.org/10.3390/ecea-3-E001>
- Gabora, L. (2017). *Honing Theory : A Complex Systems Framework for Creativity*.
- Galbraith, G. C. (1994). Two-channel brain-stem frequency-following responses to pure tone and missing fundamental stimuli. *Electroencephalography and Clinical Neurophysiology/ Evoked Potentials*, 92(4), 321-330. [https://doi.org/10.1016/0168-5597\(94\)90100-7](https://doi.org/10.1016/0168-5597(94)90100-7)
- Gallimore, A. R. (2015). Restructuring consciousness – the psychedelic state in light of integrated information theory. *Frontiers in Human Neuroscience*, 9.
<https://doi.org/10.3389/fnhum.2015.00346>

- Gamboni, D. (2002). *Potential Images*.
- Gammaitoni, L., Hänggi, P., Jung, P., & Marchesoni, F. (2009). Stochastic Resonance : A remarkable idea that changed our perception of noise. *The European Physical Journal B*, 69(1), 1-3.
<https://doi.org/10.1140/epjb/e2009-00163-x>
- Gandy, S., Bonnelle, V., Jacobs, E., & Luke, D. (2022). Psychedelics as potential catalysts of scientific creativity and insight. *Drug Science, Policy and Law*, 8, 205032452210976.
<https://doi.org/10.1177/20503245221097649>
- Gao, R., Peterson, E. J., & Voytek, B. (2017). Inferring synaptic excitation/inhibition balance from field potentials. *NeuroImage*, 158, 70-78. <https://doi.org/10.1016/j.neuroimage.2017.06.078>
- Gendlin, E. T. (1997). *Experiencing and the Creation of Meaning : A Philosophical and Psychological Approach to the Subjective*. Northwestern University Press.
- Geng, H., Xu, P., Sommer, I. E., Luo, Y.-J., Aleman, A., & Ćurčić-Blake, B. (2020). Abnormal dynamic resting-state brain network organization in auditory verbal hallucination. *Brain Structure and Function*, 225(8), 2315-2330. <https://doi.org/10.1007/s00429-020-02119-1>
- Geng, S., Zhou, W., Yuan, Q., Cai, D., & Zeng, Y. (2011). EEG non-linear feature extraction using correlation dimension and Hurst exponent. *Neurological Research*, 33(9), 908-912.
<https://doi.org/10.1179/1743132811Y.0000000041>
- Gerster, M., Waterstraat, G., Litvak, V., Lehnertz, K., Schnitzler, A., Florin, E., Curio, G., & Nikulin, V. (2022). Separating Neural Oscillations from Aperiodic 1/f Activity : Challenges and Recommendations. *Neuroinformatics*, 20(4), 991-1012. <https://doi.org/10.1007/s12021-022-09581-8>
- Gervais, C., Boucher, L.-P., Villar, G. M., Lee, U., & Duclos, C. (2023). A scoping review for building a criticality-based conceptual framework of altered states of consciousness. *Frontiers in Systems Neuroscience*, 17, 1085902. <https://doi.org/10.3389/fnsys.2023.1085902>

- Geyer, M., & Vollenweider, F. (2008). Serotonin research : Contributions to understanding psychoses. *Trends in Pharmacological Sciences*, 29(9), 445-453. <https://doi.org/10.1016/j.tips.2008.06.006>
- Ghiani, A., Maniglia, M., Battaglini, L., Melcher, D., & Ronconi, L. (2021). Binding Mechanisms in Visual Perception and Their Link With Neural Oscillations : A Review of Evidence From tACS. *Frontiers in Psychology*, 12, 643677. <https://doi.org/10.3389/fpsyg.2021.643677>
- Giehl, J., Noury, N., & Siegel, M. (2021a). Dissociating harmonic and non-harmonic phase-amplitude coupling in the human brain. *NeuroImage*, 227(December 2020). <https://doi.org/10.1016/j.neuroimage.2020.117648>
- Giehl, J., Noury, N., & Siegel, M. (2021b). Dissociating harmonic and non-harmonic phase-amplitude coupling in the human brain. *NeuroImage*, 227, 117648. <https://doi.org/10.1016/j.neuroimage.2020.117648>
- Gigerenzer, G. (2007). *Gut Feelings : The Intelligence of the Unconscious*. Penguin.
- Gilden, D. L., Schmuckler, M. A., & Clayton, K. (1993). The Perception of Natural Contour. *Psychological Review*, 100(3), 460-478. <https://doi.org/10.1037/0033-295X.100.3.460>
- Gill, K. Z., & Purves, D. (2009a). A biological rationale for musical scales. *PLoS ONE*, 4(12). <https://doi.org/10.1371/journal.pone.0008144>
- Gill, K. Z., & Purves, D. (2009b). A Biological Rationale for Musical Scales. *PLoS ONE*, 4(12), e8144. <https://doi.org/10.1371/journal.pone.0008144>
- Girn, M., Mills, C., Roseman, L., Carhart-Harris, R. L., & Christoff, K. (2020). Updating the dynamic framework of thought : Creativity and psychedelics. *NeuroImage*, 213, 116726. <https://doi.org/10.1016/j.neuroimage.2020.116726>
- Girn, M., Rosas, F. E., Daws, R. E., Gallen, C. L., Gazzaley, A., & Carhart-Harris, R. L. (2023). A complex systems perspective on psychedelic brain action. *Trends in Cognitive Sciences*, 27(5), 433-445. <https://doi.org/10.1016/j.tics.2023.01.003>

- Glăveanu, V. P. (2014). The Psychology of Creativity : A Critical Reading. *Creativity: Theories – Research – Applications*, 1(1), 10-32. <https://doi.org/10.15290/ctra.2014.01.01.02>
- Goeltzenleuchter, B., van Suchtelen, A., Brown, K. L., & Grompone, G. (2019). The Value of Creativity for Enhancing Translational Ecologies, Insights, and Discoveries. *Frontiers in Psychology*, 10. <https://www.frontiersin.org/journals/psychology/articles/10.3389/fpsyg.2019.00951>
- Gordon, N., Hohwy, J., Davidson, M. J., Van Boxtel, J. J. A., & Tsuchiya, N. (2019). From intermodulation components to visual perception and cognition-a review. *NeuroImage*, 199, 480-494. <https://doi.org/10.1016/j.neuroimage.2019.06.008>
- Gough, H. G. (1976). Studying Creativity by Means of Word Association Tests. *Journal of Applied Psychology*.
- Gourévitch, B., Martin, C., Postal, O., & Eggermont, J. J. (2020). Oscillations in the auditory system and their possible role. *Neuroscience & Biobehavioral Reviews*, 113, 507-528. <https://doi.org/10.1016/j.neubiorev.2020.03.030>
- Gramfort, A., Luessi, M., Larson, E., Engemann, D. A., Strohmeier, D., Brodbeck, C., Parkkonen, L., & Hämäläinen, M. S. (2014). MNE software for processing MEG and EEG data. *NeuroImage*, 86, 446-460. <https://doi.org/10.1016/j.neuroimage.2013.10.027>
- Gramfort, A., Luessi, M., Larson, E., Engemann, D., Strohmeier, D., Brodbeck, C., Goj, R., Jas, M., Brooks, T., Parkkonen, L., & Hämäläinen, M. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, 7. <https://www.frontiersin.org/articles/10.3389/fnins.2013.00267>
- Gregory, R. (2000). Reversing Rorschach. *Nature*, 404(6773), 19-19. <https://doi.org/10.1038/35003661>
- Griffiths, R. R., Richards, W. A., McCann, U., & Jesse, R. (2006). Psilocybin can occasion mystical-type experiences having substantial and sustained personal meaning and spiritual significance. *Psychopharmacology*, 187(3), 268-283. <https://doi.org/10.1007/s00213-006-0457-5>

- Griffiths, R., Richards, W., Johnson, M., McCann, U., & Jesse, R. (2008). Mystical-type experiences occasioned by psilocybin mediate the attribution of personal meaning and spiritual significance 14 months later. *Journal of Psychopharmacology*, 22(6), 621-632.
<https://doi.org/10.1177/0269881108094300>
- Grond, F., & Hermann, T. (2012). Aesthetic strategies in sonification. *AI and Society*, 27(2), 213-222.
<https://doi.org/10.1007/s00146-011-0341-7>
- Grosu, G. F., Hopp, A. V., Moca, V. V., Bârzan, H., Ciuparu, A., Ercsey-Ravasz, M., Winkel, M., Linde, H., & Mureşan, R. C. (2023). The fractal brain : Scale-invariance in structure and dynamics. *Cerebral Cortex*, 33(8), 4574-4605. <https://doi.org/10.1093/cercor/bhac363>
- Gruszka, A., & Necka, E. (2002). Priming and Acceptance of Close and Remote Associations by Creative and Less Creative People. *Creativity Research Journal*, 14(2), 193-205.
https://doi.org/10.1207/S15326934CRJ1402_6
- Guénin—Carlut, A. (2022). Thinking like a State : Embodied intelligence in the deep history of our collective mind. *IOP Conference Series: Materials Science and Engineering*, 1261(1), 012026.
<https://doi.org/10.1088/1757-899X/1261/1/012026>
- Guidotti, R., Del Gratta, C., Baldassarre, A., Romani, G. L., & Corbetta, M. (2015). Visual Learning Induces Changes in Resting-State fMRI Multivariate Pattern of Information. *Journal of Neuroscience*, 35(27), 9786-9798. <https://doi.org/10.1523/JNEUROSCI.3920-14.2015>
- Guilford, J. P. (1950). Creativity. American psychology. *New World Encyclopedia*, 5, 444-454.
- Guilford, J. P. (1967). Creativity : Yesterday, Today and Tomorrow. *The Journal of Creative Behavior*, 1(1), 3-14. <https://doi.org/10.1002/j.2162-6057.1967.tb00002.x>
- Hába, A. (1921). *Quatuor à cordes au système de quart de ton = im vierteltonsystem = ve čtvrttónové soustavě = on the quarter tone-systeme, op. 7.*

<https://urresearch.rochester.edu/institutionalPublicationPublicView.action?institutionalItemId=17838>

Hadjidimitriou, S., Zacharakis, A., Doulgeris, P., Panoulas, K., Hadjileontiadis, L., & Panas, S. (2010). Sensorimotor cortical response during motion reflecting audiovisual stimulation : Evidence from fractal EEG analysis. *Medical & Biological Engineering & Computing*, *48*(6), 561-572.

<https://doi.org/10.1007/s11517-010-0606-1>

Hagerhall, C. M., Purcell, T., & Taylor, R. (2004a). Fractal dimension of landscape silhouette outlines as a predictor of landscape preference. *Journal of Environmental Psychology*, *24*(2), 247-255.

<https://doi.org/10.1016/j.jenvp.2003.12.004>

Hagerhall, C. M., Purcell, T., & Taylor, R. (2004b). Fractal dimension of landscape silhouette outlines as a predictor of landscape preference. *Journal of Environmental Psychology*, *24*(2), 247-255.

<https://doi.org/10.1016/j.jenvp.2003.12.004>

Halim, Z., Baig, R., & Bashir, S. (2007). Temporal patterns analysis in EEG data using sonification. *2007 International Conference on Information and Emerging Technologies, ICIET*, 12-17.

<https://doi.org/10.1109/ICIET.2007.4381303>

Harasim, D. (2020). *The Learnability of the Grammar of Jazz : Bayesian Inference of Hierarchical Structures in Harmony*.

Hardmeier, M., Hatz, F., Bousleiman, H., Schindler, C., Stam, C. J., & Fuhr, P. (2014). Reproducibility of Functional Connectivity and Graph Measures Based on the Phase Lag Index (PLI) and Weighted Phase Lag Index (wPLI) Derived from High Resolution EEG. *PLOS ONE*, *9*(10), e108648.

<https://doi.org/10.1371/journal.pone.0108648>

Hardstone, R., Flounders, M. W., Zhu, M., & He, B. J. (2022). Frequency-specific neural signatures of perceptual content and perceptual stability. *eLife*, *11*, e78108.

<https://doi.org/10.7554/eLife.78108>

- Hargreaves, D. J. (2012). Musical imagination : Perception and production, beauty and creativity. *Psychology of Music*, 40(5), 539-557. <https://doi.org/10.1177/0305735612444893>
- Hartmann, W. M., Cariani, P. A., & Colburn, H. S. (2019). Noise edge pitch and models of pitch perception. *The Journal of the Acoustical Society of America*, 145(4), 1993-2008. <https://doi.org/10.1121/1.5093546>
- Hartogsohn, I. (2018). The Meaning-Enhancing Properties of Psychedelics and Their Mediator Role in Psychedelic Therapy, Spirituality, and Creativity. *Frontiers in Neuroscience*, 12, 129. <https://doi.org/10.3389/fnins.2018.00129>
- Heath, D., & Ventura, D. (2016a). *Before A Computer Can Draw, It Must First Learn To See*. 8.
- Heath, D., & Ventura, D. (2016b). Before a computer can draw, it must first learn to see. *Proceedings of the 7th International Conference on Computational Creativity, ICCO 2016, June*, 172-179.
- Helmuth, M., & Schedel, M. (2022). Links between sonification and generative music. *Interdisciplinary Science Reviews*, 47(2), 215-242. <https://doi.org/10.1080/03080188.2022.2035106>
- Henaoui, D., Navarrete, M., Valderrama, M., & Le Van Quyen, M. (2020). Entrainment and synchronization of brain oscillations to auditory stimulations. *Neuroscience Research*, 156, 271-278. <https://doi.org/10.1016/j.neures.2020.03.004>
- Henriksen, D., Good, J., & Mishra, P. (2015). Embodied Thinking as a Trans-disciplinary Habit of Mind. *TechTrends*, 59(1), 6-11. <https://doi.org/10.1007/s11528-014-0812-z>
- Hong, K., Chalup, S. K., King, R. A. R., & Ostwald, M. J. (2013). Scene perception using pareidolia of faces and expressions of emotion. *Proceedings of the 2013 IEEE Symposium on Computational Intelligence for Creativity and Affective Computing, CICAC 2013 - 2013 IEEE Symposium Series on Computational Intelligence, SSCI 2013, February 2013*, 79-86. <https://doi.org/10.1109/CICAC.2013.6595224>

- Huang, N. E., & Wu, Z. (2008). A review on Hilbert-Huang transform : Method and its applications to geophysical studies. *Reviews of Geophysics*, 46(2), RG2006.
<https://doi.org/10.1029/2007RG000228>
- Hunt, T. (2020). Calculating the Boundaries of Consciousness in General Resonance Theory. *Journal of Consciousness Studies*, 27, 55-80.
- Hunt, T., Schooler, J. W., & Lane, T. J. (2019). *The Easy Part of the Hard Problem : A Resonance Theory of Consciousness*. 13(October), 1-16. <https://doi.org/10.3389/fnhum.2019.00378>
- Hyafil, A., Giraud, A. L., Fontolan, L., & Gutkin, B. (2015). Neural Cross-Frequency Coupling : Connecting Architectures, Mechanisms, and Functions. *Trends in Neurosciences*, 38(11), 725-740.
<https://doi.org/10.1016/j.tins.2015.09.001>
- Ibáñez-Marcelo, E., Campioni, L., Phinyomark, A., Petri, G., & Santarcangelo, E. L. (2019). Topology highlights mesoscopic functional equivalence between imagery and perception : The case of hypnotizability. *NeuroImage*, 200, 437-449. <https://doi.org/10.1016/j.neuroimage.2019.06.044>
- Ibáñez-Molina, A. J., & Iglesias-Parro, S. (2014). Fractal characterization of internally and externally generated conscious experiences. *Brain and Cognition*, 87, 69-75.
<https://doi.org/10.1016/j.bandc.2014.03.002>
- Idaji, M. J., Zhang, J., Stephani, T., Nolte, G., Müller, K. R., Villringer, A., & Nikulin, V. V. (2022). Harmoni : A method for eliminating spurious interactions due to the harmonic components in neuronal data. *NeuroImage*, 252(March), 119053. <https://doi.org/10.1016/j.neuroimage.2022.119053>
- Idrobo-Ávila, E., Loaiza-Correa, H., Muñoz-Bolaños, F., van Noorden, L., & Vargas-Cañas, R. (2022). Development of a biofeedback system using harmonic musical intervals to control heart rate variability with a generative adversarial network. *Biomedical Signal Processing and Control*, 71, 103095. <https://doi.org/10.1016/j.bspc.2021.103095>

- Imperatori, L. S., Betta, M., Cecchetti, L., Johnson, A. C., Ricciardi, E., Siclari, F., Pietrini, P., Chennu, S., & Bernardi, G. (2018). *EEG functional connectivity metrics wPLI and wSMI account for d distinct types of brain functional interactions* [Preprint]. Neuroscience. <https://doi.org/10.1101/450270>
- Iquebal, A. S., Bukkapatnam, S., & Srinivasa, A. (2020). Change detection in complex dynamical systems using intrinsic phase and amplitude synchronization. *arXiv:1701.00610 [Physics]*.
<http://arxiv.org/abs/1701.00610>
- Isler, J. R., Grieve, P. G., Czernochowski, D., Stark, R. I., & Friedman, D. (2008). Cross-frequency phase coupling of brain rhythms during the orienting response. *Brain Research, 1232*, 163-172.
<https://doi.org/10.1016/j.brainres.2008.07.030>
- Itoh, K., Nagashima, Y., Itoh, S.-I., Diamond, P. H., Fujisawa, A., Yagi, M., & Fukuyama, A. (2005). On the bicoherence analysis of plasma turbulence. *Physics of Plasmas, 12*(10), 102301.
<https://doi.org/10.1063/1.2062627>
- Ivanov, P. C., Amaral, L. A. N., Goldberger, A. L., Havlin, S., Rosenblum, M. G., Struzik, Z., & Stanley, H. E. (1999). Multifractality in Human Heartbeat Dynamics. *Nature, 399*(6735), 461-465.
<https://doi.org/10.1038/20924>
- Jarosz, A. F., Colflesh, G. J. H., & Wiley, J. (2012). Uncorking the muse : Alcohol intoxication facilitates creative problem solving. *Consciousness and Cognition, 21*(1), 487-493.
<https://doi.org/10.1016/j.concog.2012.01.002>
- Jensen, O., & Colgin, L. L. (2007). Cross-frequency coupling between neuronal oscillations. *Trends in Cognitive Sciences, 11*(7), 267-269. <https://doi.org/10.1016/j.tics.2007.05.003>
- Johnson, D. R., Kaufman, J. C., Baker, B. S., Patterson, J. D., Barbot, B., Green, A. E., Van Hell, J., Kennedy, E., Sullivan, G. F., Taylor, C. L., Ward, T., & Beaty, R. E. (2022). Divergent semantic integration (DSI) : Extracting creativity from narratives with distributional semantic modeling. *Behavior Research Methods*. <https://doi.org/10.3758/s13428-022-01986-2>

- Johnston, B. (1975). The Corporealism of Harry Partch. *Perspectives of New Music*, 13(2), 85-97.
<https://doi.org/10.2307/832085>
- Joshi, M. K., Fabre, A., Maier, C., Brydges, T., Kiesenhofer, D., Hainzer, H., Blatt, R., & Roos, C. F. (2020). Polarization-gradient cooling of 1D and 2D ion Coulomb crystals. *New Journal of Physics*, 22(10).
<https://doi.org/10.1088/1367-2630/abb912>
- Jung, R. E. (2013). The structure of creative cognition in the human brain. *Frontiers in Human Neuroscience*, 7. <https://doi.org/10.3389/fnhum.2013.00330>
- Jung, R. E., Gasparovic, C., Chavez, R. S., Flores, R. A., Smith, S. M., Caprihan, A., & Yeo, R. A. (2009). Biochemical support for the « threshold » theory of creativity : A magnetic resonance spectroscopy study. *Journal of Neuroscience*, 29(16), 5319-5325.
<https://doi.org/10.1523/JNEUROSCI.0588-09.2009>
- Kaelen, M., Barrett, F. S., Roseman, L., Lorenz, R., Family, N., Bolstridge, M., Curran, H. V., Feilding, A., Nutt, D. J., & Carhart-Harris, R. L. (2015). LSD enhances the emotional response to music. *Psychopharmacology*, 232(19), 3607-3614. <https://doi.org/10.1007/s00213-015-4014-y>
- Kapur, S. (2003). Psychosis as a State of Aberrant Salience : A Framework Linking Biology, Phenomenology, and Pharmacology in Schizophrenia. *American Journal of Psychiatry*, 160(1), 13-23. <https://doi.org/10.1176/appi.ajp.160.1.13>
- Kapur, S., Mizrahi, R., & Li, M. (2005). From dopamine to salience to psychosis-linking biology, pharmacology and phenomenology of psychosis. *Schizophrenia Research*, 79(1), 59-68.
<https://doi.org/10.1016/j.schres.2005.01.003>
- Karkare, S., Saha, G., & Bhattacharya, J. (2009). Investigating long-range correlation properties in EEG during complex cognitive tasks. *Chaos, Solitons & Fractals*, 42(4), 2067-2073.
<https://doi.org/10.1016/j.chaos.2009.03.148>

- Katahira, K., Yamazaki, Y., Yamaoka, C., Ozaki, H., Nakagawa, S., & Nagata, N. (2018). EEG Correlates of the Flow State : A Combination of Increased Frontal Theta and Moderate Frontocentral Alpha Rhythm in the Mental Arithmetic Task. *Frontiers in Psychology, 9*.
<https://www.frontiersin.org/articles/10.3389/fpsyg.2018.00300>
- Kaufman, S. B., & Kaufman, J. C. (2009). *The Psychology of Creative Writing*. Cambridge University Press.
- Kerlleñevich, H., Riera, P. E., & Eguia, M. C. (2011). SANTIAGO - A real-time biological neural network environment for generative music creation. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 6625 LNCS(PART 2)*, 344-353. https://doi.org/10.1007/978-3-642-20520-0_35
- Keshavan, M. S., & Sudarshan, M. (2017). Deep dreaming, aberrant salience and psychosis : Connecting the dots by artificial neural networks. *Schizophrenia Research, 188*, 178-181.
<https://doi.org/10.1016/j.schres.2017.01.020>
- Kim, K. H. (2006). Can We Trust Creativity Tests? A Review of the Torrance Tests of Creative Thinking (TTCT). *Creativity Research Journal, 18*(1), 3-14. https://doi.org/10.1207/s15326934crj1801_2
- Kiou, J. L. (2018). *EMBODIMENT AND ITS EFFECTS: HOW CREATIVITY, PERCEPTION AND SENSORY PROCESSING SENSITIVITY LINK WITH EMPATHY AND THEORY OF MIND MECHANISMS*.
- Kitson, A., DiPaola, S., & Riecke, B. E. (2019). Lucid Loop : A Virtual Deep Learning Biofeedback System for Lucid Dreaming Practice. *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems*, 1-6. <https://doi.org/10.1145/3290607.3312952>
- Kleinmintz, O. M., Ivancovsky, T., & Shamay-Tsoory, S. G. (2019). The two-fold model of creativity : The neural underpinnings of the generation and evaluation of creative ideas. *Current Opinion in Behavioral Sciences, 27*, 131-138. <https://doi.org/10.1016/j.cobeha.2018.11.004>

- Klemm, W. R., Li, T. H., & Hernandez, J. L. (2000). Coherent EEG Indicators of Cognitive Binding during Ambiguous Figure Tasks. *Consciousness and Cognition*, 9(1), 66-85.
<https://doi.org/10.1006/ccog.1999.0426>
- Klimesch, W. (2013a). An algorithm for the EEG frequency architecture of consciousness and brain body coupling. *Frontiers in Human Neuroscience*, 7(NOV), 1-4.
<https://doi.org/10.3389/fnhum.2013.00766>
- Klimesch, W. (2013b). An algorithm for the EEG frequency architecture of consciousness and brain body coupling. *Frontiers in Human Neuroscience*, 7. <https://doi.org/10.3389/fnhum.2013.00766>
- Klimesch, W. (2018a). The frequency architecture of brain and brain body oscillations : An analysis. *European Journal of Neuroscience*, 48(7), 2431-2453. <https://doi.org/10.1111/ejn.14192>
- Klimesch, W. (2018b). The frequency architecture of brain and brain body oscillations : An analysis. *European Journal of Neuroscience*, 48(7), 2431-2453. <https://doi.org/10.1111/ejn.14192>
- Klinton, H. (1984). Original thinking and ambiguous. *Bulletin of the Psychonomic Society*, 22(2), 129-131.
- Klonowski, W. (2006). *Application of nonlinear dynamics in biosignal analysis* (A. M. Sergeev, Éd.; p. 59750Z-59750Z - 10). <https://doi.org/10.1117/12.675580>
- Knill, D. C., & Pouget, A. (2004). The Bayesian brain : The role of uncertainty in neural coding and computation. *Trends in Neurosciences*, 27(12), 712-719.
<https://doi.org/10.1016/j.tins.2004.10.007>
- Koffka, K. (2013). *Principles Of Gestalt Psychology*. Routledge.
- Kok, P., Rahnev, D., Jehee, J. F. M., Lau, H. C., & De Lange, F. P. (2012). Attention Reverses the Effect of Prediction in Silencing Sensory Signals. *Cerebral Cortex*, 22(9), 2197-2206.
<https://doi.org/10.1093/cercor/bhr310>

- Kolekar, M. H., Talbar, S. N., & Sontakke, T. R. (2000). Texture segmentation using fractal signature. *IETE Journal of Research*, 46(5), 319-323. <https://doi.org/10.1080/03772063.2000.11416172>
- Kornmeier, J., & Bach, M. (2012). Ambiguous Figures – What Happens in the Brain When Perception Changes But Not the Stimulus. *Frontiers in Human Neuroscience*, 6. <https://www.frontiersin.org/articles/10.3389/fnhum.2012.00051>
- Köster, C. (2009). The concept of electrostatic non-orbital harmonic ion trapping. *International Journal of Mass Spectrometry*, 287(1-3), 114-118. <https://doi.org/10.1016/j.ijms.2009.01.014>
- Kramer, G., Walker, B., Bonebright, T., Cook, P., & Flowers, J. H. (2010). Sonification Report : Status of the Field and Research Agenda. *Faculty Publications, Department of Psychology, University of Nebraska, March*, 1-29.
- Kruse, P., & Stadler, M. (2012). *Ambiguity in Mind and Nature : Multistable Cognitive Phenomena*. Springer Science & Business Media.
- Kuang, C., Chen, J., Chen, J., Shi, Y., Huang, H., Jiao, B., Lin, Q., Rao, Y., Liu, W., Zhu, Y., Mo, L., Ma, L., & Lin, J. (2022). Uncovering neural distinctions and commodities between two creativity subsets : A meta-analysis of fMRI studies in divergent thinking and insight using activation likelihood estimation. *Human Brain Mapping*, 43(16), 4864-4885. <https://doi.org/10.1002/hbm.26029>
- Kwiatkowski, J., Vartanian, O., & Martindale, C. (1999). *Creativity and Speed of Mental Processing*. <https://journals.sagepub.com/doi/abs/10.2190/2Q5D-TY7X-37QE-2RY2>
- La Rocca, D., Zilber, N., Abry, P., van Wassenhove, V., & Ciuciu, P. (2018). Self-similarity and multifractality in human brain activity : A wavelet-based analysis of scale-free brain dynamics. *Journal of Neuroscience Methods*, 309, 175-187. <https://doi.org/10.1016/j.jneumeth.2018.09.010>

- Lang, D. J., Wiek, A., Bergmann, M., Stauffacher, M., Martens, P., Moll, P., Swilling, M., & Thomas, C. J. (2012). Transdisciplinary research in sustainability science : Practice, principles, and challenges. *Sustainability Science*, 7(1), 25-43. <https://doi.org/10.1007/s11625-011-0149-x>
- Langner, G. (1992). Periodicity coding in the auditory system. *Hearing Research*, 60(2), 115-142. [https://doi.org/10.1016/0378-5955\(92\)90015-F](https://doi.org/10.1016/0378-5955(92)90015-F)
- Lebedev, A. V., Kaelen, M., Lövdén, M., Nilsson, J., Feilding, A., Nutt, D. J., & Carhart-Harris, R. L. (2016). LSD-induced entropic brain activity predicts subsequent personality change. *Human Brain Mapping*, 37(9), 3203-3213. <https://doi.org/10.1002/hbm.23234>
- Lee, J. (2016). I see faces : Popular pareidolia and the proliferation of meaning. *Materiality and Popular Culture: The Popular Life of Things*, 105-118. <https://doi.org/10.4324/9781315621166>
- Lee, K. M., Skoe, E., Kraus, N., & Ashley, R. (2009). Selective subcortical enhancement of musical intervals in musicians. *Journal of Neuroscience*, 29(18), 5832-5840. <https://doi.org/10.1523/JNEUROSCI.6133-08.2009>
- Lee, K. M., Skoe, E., Kraus, N., & Ashley, R. (2015). Neural transformation of dissonant intervals in the auditory brainstem. *Music Perception*, 32(5), 445-459. <https://doi.org/10.1525/MP.2015.32.5.445>
- Lehar, S. (2003). Gestalt isomorphism and the primacy of subjective conscious experience : A Gestalt Bubble model. *Behavioral and Brain Sciences*, 26(4), 375-408. <https://doi.org/10.1017/S0140525X03000098>
- Lempel, A., & Ziv, J. (1976). On the Complexity of Finite Sequences. *IEEE Transactions on Information Theory*, 22(1), 75-81. <https://doi.org/10.1109/TIT.1976.1055501>
- Lennon, J. J. (2000a). Red-shifts and red herrings in geographical ecology. *Ecography*, 23(1), 101-113. <https://doi.org/10.1111/j.1600-0587.2000.tb00265.x>

- Lennon, J. J. (2000b). Red-shifts and red herrings in geographical ecology. *Ecography*, 23(1), 101-113.
<https://doi.org/10.1111/j.1600-0587.2000.tb00265.x>
- Leong, D. (2012). *Thinking through the body – a multimodal perspective*.
- Lerud, K. D., Almonte, F. V., Kim, J. C., & Large, E. W. (2014). Mode-locking neurodynamics predict human auditory brainstem responses to musical intervals. *Hearing Research*, 308, 41-49.
<https://doi.org/10.1016/j.heares.2013.09.010>
- Levinson, S. C. (2000). *Presumptive Meanings : The Theory of Generalized Conversational Implicature*. MIT Press.
- Levitin, D. J., Chordia, P., & Menon, V. (2012a). Musical rhythm spectra from Bach to Joplin obey a 1/f power law. *Proceedings of the National Academy of Sciences*, 109(10), 3716-3720.
<https://doi.org/10.1073/pnas.1113828109>
- Levitin, D. J., Chordia, P., & Menon, V. (2012b). Musical rhythm spectra from Bach to Joplin obey a 1/f power law. *Proceedings of the National Academy of Sciences of the United States of America*, 109(10), 3716-3720. <https://doi.org/10.1073/pnas.1113828109>
- Lewicki, M. S. (2002). Efficient coding of natural sounds. *Nature Neuroscience*, 5(4), 356-363.
<https://doi.org/10.1038/nn831>
- Li, J., Sun, C., & Du, Q. (2006). A New Box-Counting Method for Estimation of Image Fractal Dimension. *2006 International Conference on Image Processing*, 3029-3032.
<https://doi.org/10.1109/ICIP.2006.313005>
- Linares, D., Aguilar-Lleyda, D., & López-Moliner, J. (2019). Decoupling sensory from decisional choice biases in perceptual decision making. *eLife*, 8, e43994. <https://doi.org/10.7554/eLife.43994>
- Lisman, J. E., & Idiart, M. A. P. (1995). Storage of 7 ± 2 Short-Term Memories in Oscillatory Subcycles. *Science*, 267(5203), 1512-1515. <https://doi.org/10.1126/science.7878473>

- Liu, J., Li, J., Feng, L., Li, L., Tian, J., & Lee, K. (2014a). Seeing Jesus in toast : Neural and behavioral correlates of face pareidolia. *Cortex*, *53*, 60-77. <https://doi.org/10.1016/j.cortex.2014.01.013>
- Liu, J., Li, J., Feng, L., Li, L., Tian, J., & Lee, K. (2014b). Seeing Jesus in toast : Neural and behavioral correlates of face pareidolia. *Cortex*, *53*(1), 60-77. <https://doi.org/10.1016/j.cortex.2014.01.013>
- Lloyd-Cox, J., Chen, Q., & Beaty, R. E. (2022). The time course of creativity : Multivariate classification of default and executive network contributions to creative cognition over time. *Cortex*, *156*, 90-105. <https://doi.org/10.1016/j.cortex.2022.08.008>
- Lopata, J. A., Barr, N., Slayton, M., & Seli, P. (2022). Dual-modes of creative thought in the classroom : Implications of network neuroscience for creativity education. *Translational Issues in Psychological Science*.
- Lopes, R., & Betrouni, N. (2009). Fractal and multifractal analysis : A review. *Medical Image Analysis*, *13*(4), 634-649. <https://doi.org/10.1016/j.media.2009.05.003>
- López, M. E., Pusil, S., Pereda, E., Maestú, F., & Barceló, F. (2019). Dynamic low frequency EEG phase synchronization patterns during proactive control of task switching. *NeuroImage*, *186*, 70-82. <https://doi.org/10.1016/j.neuroimage.2018.10.068>
- Lots, I. S., & Stone, L. (2008). Perception of musical consonance and dissonance : An outcome of neural synchronization. *Journal of the Royal Society Interface*, *5*(29), 1429-1434. <https://doi.org/10.1098/rsif.2008.0143>
- Lutz, A. (2002). Toward a neurophenomenology as an account of generative passages : A first empirical case study. In *NEUROPHENOMENOLOGY AS AN ACCOUNT OF GENERATIVE PASSAGES Phenomenology and the Cognitive Sciences* (Vol. 1, p. 133-167).
- Lutz, A., & Thompson, E. (2003). Neurophenomenology : Integrating subjective experience and brain dynamics in the neuroscience of consciousness. *Journal of Consciousness Studies*, *9-10*, 31-52. <https://doi.org/10.1023/A:1020320221083>

- Lutzenberger, W., Elbert, T., Birbaumer, N., Ray, W. J., & Schupp, H. (1992). The scalp distribution of the fractal dimension of the EEG and its variation with mental tasks. *Brain Topography*, *5*(1), 27-34. <https://doi.org/10.1007/BF01129967>
- Lynn, S. J., & Rhue, J. W. (1986). The fantasy-prone person : Hypnosis, imagination, and creativity. *Journal of Personality and Social Psychology*, *51*(2), 404-408. <https://doi.org/10.1037/0022-3514.51.2.404>
- Madni, A. M. (2007). TRANSDISCIPLINARITY : REACHING BEYOND DISCIPLINES TO FIND CONNECTIONS. *Journal of Integrated Design and Process Science*, *11*(1), 1-11.
- Makowski, D., Pham, T., Lau, Z. J., Brammer, J. C., Lespinasse, F., Pham, H., Schölzel, C., & Chen, S. H. A. (2021). NeuroKit2 : A Python toolbox for neurophysiological signal processing. *Behavior Research Methods*. <https://doi.org/10.3758/s13428-020-01516-y>
- Maksimenko, V. A., Kuc, A., Frolov, N. S., Khramova, M. V., Pisarchik, A. N., & Hramov, A. E. (2020). Dissociating Cognitive Processes During Ambiguous Information Processing in Perceptual Decision-Making. *Frontiers in Behavioral Neuroscience*, *14*, 95. <https://doi.org/10.3389/fnbeh.2020.00095>
- Malinin, L. H. (2019). How Radical Is Embodied Creativity? Implications of 4E Approaches for Creativity Research and Teaching. *Frontiers in Psychology*, *10*. <https://doi.org/10.3389/fpsyg.2019.02372>
- Mathes, B., Khalaidovski, K., Schmiedt-Fehr, C., & Basar-Eroglu, C. (2014). Frontal theta activity is pronounced during illusory perception. *International Journal of Psychophysiology*, *94*(3), 445-454. <https://doi.org/10.1016/j.ijpsycho.2014.08.585>
- Mathys, C., Daunizeau, J., Friston, K. J., & Stephan, K. E. (2011). A Bayesian foundation for individual learning under uncertainty. *Frontiers in Human Neuroscience*, *5*(MAY), 9. <https://doi.org/10.3389/fnhum.2011.00039>

- McCaig, G., DiPaola, S., & Gabora, L. (2016). *Deep Convolutional Networks as Models of Generalization and Blending Within Visual Creativity*. 8.
- McFee, B., Raffel, C., Liang, D., Ellis, D., McVicar, M., Battenberg, E., & Nieto, O. (2015). *librosa : Audio and Music Signal Analysis in Python*. 18-24. <https://doi.org/10.25080/Majora-7b98e3ed-003>
- Mcgurk, H., & Macdonald, J. (1976). Hearing lips and seeing voices. *Nature*, 264(5588), Article 5588. <https://doi.org/10.1038/264746a0>
- Mckinney, M. F., Tramo, M. J., & Delgutte, B. (2001). Neural correlates of musical dissonance in the inferior colliculus. *Physiological and Psychophysical Bases of Auditory Function*, 71-87.
- Mediano, P. A. M., Rosas, F. E., Timmermann, C., Roseman, L., Nutt, D. J., Feilding, A., Kaelen, M., Kringelbach, M. L., Barrett, A. B., Seth, A. K., Muthukumaraswamy, S., Bor, D., & Carhart-Harris, R. L. (2020). *Effects of external stimulation on psychedelic state neurodynamics* [Preprint]. Neuroscience. <https://doi.org/10.1101/2020.11.01.356071>
- Mednick, S. (1962). The associative basis of the creative process. *Psychological Review*, 69(3), 220-232. <https://doi.org/10.1037/h0048850>
- Mehta, R., Zhu, R. (Juliet), & Cheema, A. (2012). Is Noise Always Bad? Exploring the Effects of Ambient Noise on Creative Cognition. *Journal of Consumer Research*, 39(4), 784-799. <https://doi.org/10.1086/665048>
- Mendelsohn, G. A., & Griswold, B. B. (1964). Differential use of incidental stimuli in problem solving as a function of creativity. *The Journal of Abnormal and Social Psychology*, 68(4), 431-436. <https://doi.org/10.1037/h0040166>
- Meneveau, C., & Sreenivasan, K. R. (1991). The multifractal nature of turbulent energy dissipation. *Journal of Fluid Mechanics*, 224, 429-484. <https://doi.org/10.1017/S0022112091001830>
- Merleau-Ponty, M. (1965). *Phenomenology of perception*.

- Merleau-Ponty, M. (1969). *La prose du monde* (Librairie Gallimard PARIS). <https://www.librairie-gallimard.com/livre/9782070728442-la-prose-du-monde-maurice-merleau-ponty/>
- Meschiari, M. (2009). Roots of the savage mind : Apophenia and imagination as cognitive process. *Quaderni di semantica: rivista internazionale di semantica teorica e applicata*, 30(2), 183-262.
- Messaritaki, E., Koelewijn, L., Dima, D. C., Williams, G. M., Perry, G., & Singh, K. D. (2017). Assessment and elimination of the effects of head movement on MEG resting-state measures of oscillatory brain activity. *NeuroImage*, 159, 302-324. <https://doi.org/10.1016/j.neuroimage.2017.07.038>
- Micheyl, C., Keebler, M. V., & Oxenham, A. J. (2010). Pitch perception for mixtures of spectrally overlapping harmonic complex tones. *The Journal of the Acoustical Society of America*, 128(1), 257-269. <https://doi.org/10.1121/1.3372751>
- Mierau, A., Klimesch, W., & Lefebvre, J. (2017). State-dependent alpha peak frequency shifts : Experimental evidence, potential mechanisms and functional implications. *Neuroscience*, 360, 146-154. <https://doi.org/10.1016/j.neuroscience.2017.07.037>
- Millière, R., Carhart-Harris, R. L., Roseman, L., Trautwein, F.-M., & Berkovich-Ohana, A. (2018). Psychedelics, Meditation, and Self-Consciousness. *Frontiers in Psychology*, 9, 1475. <https://doi.org/10.3389/fpsyg.2018.01475>
- Milne, A. (2018). *Linking Sonic Aesthetics with Mathematical Theories* (R. T. Dean & A. McLean, Éds.; Vol. 1). Oxford University Press. <https://doi.org/10.1093/oxfordhb/9780190226992.013.6>
- Milne, A. J. (2013). *A computational model of the cognition of tonality*. <https://doi.org/10.13140/2.1.4958.3044>
- Milthorp, R. (2003). *SELF-NARRATIVE AND THE PLAY OF ADHD AND CREATIVITY*.
- Minami, T., Noritake, Y., & Nakauchi, S. (2014). Decreased beta-band activity is correlated with disambiguation of hidden figures. *Neuropsychologia*, 56, 9-16. <https://doi.org/10.1016/j.neuropsychologia.2013.12.026>

- Miranda, E. R. (2006). Brain-Computer music interface for composition and performance. *International Journal on Disability and Human Development*, 5(2), 119-126.
<https://doi.org/10.1515/IJDHD.2006.5.2.119>
- Moisello, C., Meziane, H. B., Kelly, S., Perfetti, B., Kvint, S., Voutsinas, N., Blanco, D., Quartarone, A., Tononi, G., & Ghilardi, M. F. (2013). Neural Activations during Visual Sequence Learning Leave a Trace in Post-Training Spontaneous EEG. *PLoS ONE*, 8(6), e65882.
<https://doi.org/10.1371/journal.pone.0065882>
- Mölle, M., Marshall, L., Wolf, B., Fehm, H. L., & Born, J. (1999). EEG complexity and performance measures of creative thinking. *Psychophysiology*, 36(1), 95-104.
<https://doi.org/10.1017/S0048577299961619>
- Mori, M., MacDorman, K., & Kageki, N. (2012). The Uncanny Valley [From the Field]. *IEEE Robotics & Automation Magazine*, 19(2), 98-100. <https://doi.org/10.1109/MRA.2012.2192811>
- Moss, F. (2004). Stochastic resonance and sensory information processing : A tutorial and review of application. *Clinical Neurophysiology*, 115(2), 267-281.
<https://doi.org/10.1016/j.clinph.2003.09.014>
- Moss, F., Ward, L. M., & Sannita, W. G. (2004). Stochastic resonance and sensory information processing : A tutorial and review of application. *Clinical Neurophysiology*.
<https://doi.org/10.1016/j.clinph.2003.09.014>
- Motamedi-Fakhr, S., Moshrefi-Torbati, M., Hill, M., Hill, C. M., & White, P. R. (2014). Signal processing techniques applied to human sleep EEG signals—A review. *Biomedical Signal Processing and Control*, 10, 21-33. <https://doi.org/10.1016/j.bspc.2013.12.003>
- Mottron, L., Dawson, M., & Soulières, I. (2009). Enhanced perception in savant syndrome : Patterns, structure and creativity. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 364(1522), 1385-1391. <https://doi.org/10.1098/rstb.2008.0333>

- Muthukumaraswamy, S. D., & Liley, D. T. (2017). *Modification of scale-free electrophysiological activity induced by changes in excitatory-inhibitory balance is governed by the dynamics of multiple oscillatory relaxation processes*. <https://doi.org/10.1101/203786>
- Nakatani, H., & Leeuwen, C. van. (2005). Individual differences in perceptual switching rates; the role of occipital alpha and frontal theta band activity. *Biological Cybernetics*, 93(5), 343-354.
<https://doi.org/10.1007/s00422-005-0011-2>
- Narushima, T. (2017). *Microtonality and the Tuning Systems of Erv Wilson* (1^{re} éd.). Routledge.
<https://doi.org/10.4324/9781315718583>
- Natarajan, K., Tiboleng, T., & Puthusserypady, S. K. (2004). Nonlinear analysis of EEG signals at different mental states. *BioMedical Engineering OnLine*, 11.
- Nęcka, E. (2011). Perception and Creativity. In *Encyclopedia of Creativity* (p. 216-219). Elsevier.
<https://doi.org/10.1016/B978-0-12-375038-9.00167-9>
- Nees, M. A., & Phillips, C. (2015). Auditory Pareidolia : Effects of Contextual Priming on Perceptions of Purportedly Paranormal and Ambiguous Auditory Stimuli: Auditory pareidolia. *Applied Cognitive Psychology*, 29(1), 129-134. <https://doi.org/10.1002/acp.3068>
- Nelli, S., Malpani, A., Boonjindasup, M., & Serences, J. T. (2021). Individual Alpha Frequency Determines the Impact of Bottom-Up Drive on Visual Processing. *Cerebral Cortex Communications*, 2(2), tgab032. <https://doi.org/10.1093/texcom/tgab032>
- Nelson, B., & Rawlings, D. (2009a). How Does It Feel? The Development of the Experience of Creativity Questionnaire. *Creativity Research Journal*, 21(1), 43-53.
<https://doi.org/10.1080/10400410802633442>
- Nelson, B., & Rawlings, D. (2009b). How does it feel ? The development of the experience of creativity questionnaire. *Creativity Research Journal*, 21(1), 43-53.
<https://doi.org/10.1080/10400410802633442>

- Nelson, C. B. (2005). *The Creative Process : A Phenomenological and Psychometric Investigation of Artistic Creativity*. 1-417.
- Neubauer, A. C., & Fink, A. (2009). Intelligence and neural efficiency : Measures of brain activation versus measures of functional connectivity in the brain. *Intelligence*, 37(2), 223-229.
<https://doi.org/10.1016/j.intell.2008.10.008>
- Neuhäuser, M., & Hothorn, L. (2006). Maximum Tests are Adaptive Permutation Tests. *Journal of Modern Applied Statistical Methods*. <https://jmasm.com/index.php/jmasm/article/view/247>
- Nguyen, A., Yosinski, J., & Clune, J. (2016). *Multifaceted Feature Visualization : Uncovering the Different Types of Features Learned By Each Neuron in Deep Neural Networks* (arXiv:1602.03616). arXiv.
<http://arxiv.org/abs/1602.03616>
- Nijstad, B. A., De Dreu, C. K. W., Rietzschel, E. F., & Baas, M. (2010). The dual pathway to creativity model : Creative ideation as a function of flexibility and persistence. *European Review of Social Psychology*, 21(1), 34-77. <https://doi.org/10.1080/10463281003765323>
- O'Byrne, J., & Jerbi, K. (2022a). How critical is brain criticality? *Trends in Neurosciences*, 45(11), 820-837.
<https://doi.org/10.1016/j.tins.2022.08.007>
- O'Byrne, J., & Jerbi, K. (2022b). How critical is brain criticality ? *Trends in Neurosciences*, 1-18.
<https://doi.org/10.1016/j.tins.2022.08.007>
- Olson, J. A., Nahas, J., Chmoulevitch, D., Cropper, S. J., & Webb, M. E. (2021). Naming unrelated words predicts creativity. *Proceedings of the National Academy of Sciences*, 118(25), e2022340118.
<https://doi.org/10.1073/pnas.2022340118>
- O'Reilly, T., Dunbar, R., & Bentall, R. (2001). Schizotypy and creativity : An evolutionary connection? *Personality and Individual Differences*, 31(7), 1067-1078. [https://doi.org/10.1016/S0191-8869\(00\)00204-X](https://doi.org/10.1016/S0191-8869(00)00204-X)

Orłowski, P., & Bola, M. (2023). Sensory modality defines the relation between EEG Lempel–Ziv diversity and meaningfulness of a stimulus. *Scientific Reports*, *13*(1), Article 1.

<https://doi.org/10.1038/s41598-023-30639-3>

Oxford Dictionary. (2022). *imagination, n. Meanings, etymology and more | Oxford English Dictionary*.

https://www.oed.com/dictionary/imagination_n?tl=true&tab=meaning_and_use-paywall

Pahnke, W. N., & Richards, W. A. (1966). *IMPLICATIONS OF LSD AND EXPERIMENTAL MYSTICISM*'.

Palva, J. M., & Palva, S. (2018). Functional integration across oscillation frequencies by cross-frequency phase synchronization. *European Journal of Neuroscience*, *48*(7), 2399-2406.

<https://doi.org/10.1111/ejn.13767>

Palva, J. M., Palva, S., & Kaila, K. (2005). Phase Synchrony among Neuronal Oscillations in the Human Cortex. *The Journal of Neuroscience*, *25*(15), 3962-3972.

<https://doi.org/10.1523/JNEUROSCI.4250-04.2005>

Pandya, P. K., & Krishnan, A. (2004). Human frequency-following response correlates of the distortion product at 2F1-F2. *Journal of the American Academy of Audiology*, *15*(3), 184-197.

<https://doi.org/10.3766/jaaa.15.3.2>

Parker, F. (2023). Pattern and Form : Pareidolia as a Substratum to Creativity and Belief. *Alternative Spirituality and Religion Review*. <https://doi.org/10.5840/asrr2023915102>

Pascual-Leone, A., & Walsh, V. (2001). Fast Backprojections from the Motion to the Primary Visual Area Necessary for Visual Awareness. *Science*, *292*(5516), 510-512.

<https://doi.org/10.1126/science.1057099>

Patrício, P. (2012). *FROM THE SHEPARD TONE TO THE PERPETUAL MELODY AUDITORY ILLUSION*.

Pearce, B. J., Deutsch, L., Fry, P., Marafatto, F. F., & Lieu, J. (2022). Going beyond the AHA! moment : Insight discovery for transdisciplinary research and learning. *Humanities and Social Sciences Communications*, *9*(1), Article 1. <https://doi.org/10.1057/s41599-022-01129-0>

- Pearce, M. T., Zaidel, D. W., Vartanian, O., Skov, M., Leder, H., Chatterjee, A., & Nadal, M. (2016). Neuroaesthetics : The Cognitive Neuroscience of Aesthetic Experience. *Perspectives on Psychological Science*, 11(2), 265-279. <https://doi.org/10.1177/1745691615621274>
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., & Cournapeau, D. (2011). Scikit-learn : Machine Learning in Python. *Journal of Machine Learning Research*, 12.
- Pelaprat, E., & Cole, M. (2011). "Minding the Gap" : Imagination, Creativity and Human Cognition. *Integrative Psychological and Behavioral Science*, 45(4), 397-418. <https://doi.org/10.1007/s12124-011-9176-5>
- Peli, E. (1990). Contrast in complex images. *JOSA A*, 7(10), 2032-2040. <https://doi.org/10.1364/JOSAA.7.002032>
- Pennington, J., Richard, S., & Manning, C. D. (2014). GloVe : Global Vectors for Word Representation Jeffrey. *Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP)*.
- Pennisi, P., Giallongo, L., Milintenda, G., & Cannarozzo, M. (2021). Autism, autistic traits and creativity : A systematic review and meta-analysis. *Cognitive Processing*, 22(1), 1-36. <https://doi.org/10.1007/s10339-020-00992-6>
- Pentland, A. P. (1984). Fractal-Based Description of Natural Scenes. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, PAMI-6(6), 661-674. <https://doi.org/10.1109/TPAMI.1984.4767591>
- Pereira, Á., & Tschimmel, K. (2012). The design of narrative jewelry as a perception in action process. *ICDC 2012 - 2nd International Conference on Design Creativity, Proceedings, 1 DS73*(September), 97-106.

- Peretz, I., & Zatorre, R. J. (2005). Brain Organization for Music Processing. *Annual Review of Psychology*, 56(1), 89-114. <https://doi.org/10.1146/annurev.psych.56.091103.070225>
- Petchkovsky, L. (2008). Some preliminary Reflections on the Biological Substrate of meaning-making the Uses of subjective experience. *The Uses of subjective experience. Proceedings of the Conference 'The Uses of Subjective Experience: A Weekend of Conversations between ANZSJA Analysts and Academics who Work with Jung's Ideas*, 20-21.
- Petitot, J., Varela, francisco J., Pachoud, B., & Roy, J.-M. (Éds.). (2000). *Naturalizing Phenomenology : Issues in Contemporary Phenomenology and Cognitive Science*. Stanford University Press. <https://doi.org/10.1515/9781503617421>
- Petoukhov, S., Petukhova, E., & Svirin, V. (2021). Algebraic harmony in genomes of higher and lower organisms. Non-euclidean biosymmetries. *IOP Conference Series: Materials Science and Engineering*, 1129(1), 012046. <https://doi.org/10.1088/1757-899X/1129/1/012046>
- Pink-Hashkes, S., PinkHashkes, S., van Rooij, I., & Kwisthout, J. (2017). *Perception is in the Details : A Predictive Coding Account of the Psychedelic Phenomenon*. 6.
- Plamondon, J., Milne, A., & Sethares, W. A. (2009). Dynamic Tonality : Extending the Framework of Tonality into the 21st Century. *Proc. of the Annual ... , March*. <https://doi.org/10.13140/2.1.3101.1849>
- Plucker, J. A., Qian, M., & Wang, S. (2011). Is Originality in the Eye of the Beholder? Comparison of Scoring Techniques in the Assessment of Divergent Thinking. *The Journal of Creative Behavior*, 45(1), 1-22. <https://doi.org/10.1002/j.2162-6057.2011.tb01081.x>
- Policastro, E. (1995). Creative Intuition : An Integrative Review. *Creativity Research Journal*, 8(2), 99-113. https://doi.org/10.1207/s15326934crj0802_1
- Preller, K. H., Herdener, M., Pokorny, T., Planzer, A., Kraehenmann, R., Stämpfli, P., Liechti, M. E., Seifritz, E., & Vollenweider, F. X. (2017). The Fabric of Meaning and Subjective Effects in LSD-Induced

- States Depend on Serotonin 2A Receptor Activation. *Current Biology*, 27(3), 451-457.
<https://doi.org/10.1016/j.cub.2016.12.030>
- Preller, K. H., & Vollenweider, F. X. (2016). Phenomenology, Structure, and Dynamic of Psychedelic States. In A. L. Halberstadt, F. X. Vollenweider, & D. E. Nichols (Éds.), *Behavioral Neurobiology of Psychedelic Drugs* (Vol. 36, p. 221-256). Springer Berlin Heidelberg.
https://doi.org/10.1007/7854_2016_459
- Pressnitzer, D., Suied, C., & Shamma, S. (2011). Auditory scene analysis : The sweet music of ambiguity. *Frontiers in Human Neuroscience*, 5.
<https://www.frontiersin.org/articles/10.3389/fnhum.2011.00158>
- Pritchard, W. S., & Duke, D. W. (1992). Measuring chaos in the brain : A tutorial review of nonlinear dynamical eeg analysis. *International Journal of Neuroscience*, 67(1-4), 31-80.
<https://doi.org/10.3109/00207459208994774>
- Prochazkova, L., Lippelt, D. P., Colzato, L. S., Kuchar, M., Sjoerds, Z., & Hommel, B. (2018). Exploring the effect of microdosing psychedelics on creativity in an open-label natural setting. *Psychopharmacology*, 235(12), 3401-3413. <https://doi.org/10.1007/s00213-018-5049-7>
- Przyczyna, D., Przybylski, M., & Strzelecki, M. (2020). Information , communication and music : Recognition of musical dissonance and consonance in a simple reservoir computing system. *arXiv*, 1-20.
- Puckette, M. (2007). *The Theory And Techniques Of Electronic Music*. World Scientific Publishing Company.
- Purcell, D. W., Ross (B), B., Picton, T. W., & Pantev, C. (2007). Cortical responses to the 2f1-f2 combination tone measured indirectly using magnetoencephalography. *The Journal of the Acoustical Society of America*, 122(2), 992-1003. <https://doi.org/10.1121/1.2751250>

- Qi, Y., & Hillman, R. E. (1997). Temporal and spectral estimations of harmonics-to-noise ratio in human voice signals. *The Journal of the Acoustical Society of America*, *102*(1), 537-543.
<https://doi.org/10.1121/1.419726>
- Quinn, A., Lopes-dos-Santos, V., Dupret, D., Nobre, A., & Woolrich, M. (2021). EMD : Empirical Mode Decomposition and Hilbert-Huang Spectral Analyses in Python. *Journal of Open Source Software*, *6*(59), 2977. <https://doi.org/10.21105/joss.02977>
- Raami, A. (2015). *Intuition unleashed : On the application and development of intuition in the creative process*. School of Art and Design.
- Radel, R., Davranche, K., Fournier, M., & Dietrich, A. (2015). The role of (dis)inhibition in creativity : Decreased inhibition improves idea generation. *Cognition*, *134*, 110-120.
<https://doi.org/10.1016/j.cognition.2014.09.001>
- Raichle, M. E. (2015). The Brain's Default Mode Network. *Annual Review of Neuroscience*, *38*(1), 433-447. <https://doi.org/10.1146/annurev-neuro-071013-014030>
- Ramachandran, V. S., & Hirstein, W. (1999). The science of art : A neurological theory of aesthetic experience. *Journal of Consciousness Studies*, *6*(6-7), 15-51.
- Ramstead, M. J. D. (2015). Naturalizing what ? Varieties of naturalism and transcendental phenomenology. *Phenomenology and the Cognitive Sciences*, *14*(4), 929-971.
<https://doi.org/10.1007/s11097-014-9385-8>
- Ramstead, M. J. D., Seth, A. K., Hesp, C., Sandved-Smith, L., Mago, J., Lifshitz, M., Pagnoni, G., Smith, R., Dumas, G., Lutz, A., Friston, K., & Constant, A. (2022). From Generative Models to Generative Passages : A Computational Approach to (Neuro) Phenomenology. *Review of Philosophy and Psychology*. <https://doi.org/10.1007/S13164-021-00604-Y>
- Rasch, R. A. (1984). Theory of Helmholtz-Beat Frequencies. *Music Perception*, *1*(3), 308-322.
<https://doi.org/10.2307/40285263>

- Rassi, E., Dorffner, G., Gruber, W., Schabus, M., & Klimesch, W. (2019). Coupling and Decoupling between Brain and Body Oscillations. *Neuroscience Letters*, 711(January).
<https://doi.org/10.1016/j.neulet.2019.134401>
- Rastelli, C., Greco, A., Kenett, Y. N., Finocchiaro, C., & De Pisapia, N. (2022). Simulated visual hallucinations in virtual reality enhance cognitive flexibility. *Scientific Reports*, 12(1), 4027.
<https://doi.org/10.1038/s41598-022-08047-w>
- Rawlings, D. (1985). *Psychoticism, creativity and dichotic shadowing*.
<https://www.sciencedirect.com/science/article/abs/pii/0191886985900844>
- Reinhard, J. (2011). *8th Octave Overtone Tuning by 8 th Octave Overtone Tuning*.
- Reiter-Palmon, R., Forthmann, B., & Barbot, B. (2019). Scoring divergent thinking tests : A review and systematic framework. *Psychology of Aesthetics, Creativity, and the Arts*, 13(2), 144-152.
<https://doi.org/10.1037/aca0000227>
- Rekow, D., Baudouin, J. Y., Brochard, R., Rossion, B., & Leleu, A. (2022). Rapid neural categorization of facelike objects predicts the perceptual awareness of a face (face pareidolia). *Cognition*, 222(December 2021), 105016. <https://doi.org/10.1016/j.cognition.2022.105016>
- Rhodes, C., Lewis, D., & Müllensiefen, D. (2009). Bayesian model selection for harmonic labelling. *Communications in Computer and Information Science*, 37 CCIS, 107-116.
https://doi.org/10.1007/978-3-642-04579-0_11
- Ribeiro, T. L., Chialvo, D. R., & Plenz, D. (2021). Scale-Free Dynamics in Animal Groups and Brain Networks. *Frontiers in Systems Neuroscience*, 14, 591210.
<https://doi.org/10.3389/fnsys.2020.591210>
- Richards, R. (2001). Millennium as Opportunity : Chaos, Creativity, and Guilford's Structure of Intellect Model. *Creativity Research Journal*, 13(3-4), 249-265.
https://doi.org/10.1207/S15326934CRJ1334_03

- Rilling, G., Flandrin, P., & Goncalves, P. (2003a). On empirical mode decomposition and its algorithms. *IEEE-EURASIP workshop on nonlinear signal and image processing*, 3, 8-11.
- Rilling, G., Flandrin, P., & Goncalves, P. (2003b). ON EMPIRICAL MODE DECOMPOSITION AND ITS ALGORITHMS. *IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing*.
- Riquelme, H. (2002). Can People Creative in Imagery Interpret Ambiguous Figures Faster than People Less Creative in Imagery? *The Journal of Creative Behavior*, 36(2), 105-116.
<https://doi.org/10.1002/j.2162-6057.2002.tb01059.x>
- Ro, T., Breitmeyer, B., Burton, P., Singhal, N. S., & Lane, D. (2003). Feedback Contributions to Visual Awareness in Human Occipital Cortex. *Current Biology*, 13(12), 1038-1041.
[https://doi.org/10.1016/S0960-9822\(03\)00337-3](https://doi.org/10.1016/S0960-9822(03)00337-3)
- Ro, W., & Kwon, Y. (2009). 1/f Noise analysis of songs in various genre of music. *Chaos, Solitons & Fractals*, 42(4), 2305-2311. <https://doi.org/10.1016/j.chaos.2009.03.129>
- Roddy, S., & Furlong, D. (2014). Embodied Aesthetics in Auditory Display. *Organised Sound*, 19(1), 70-77.
<https://doi.org/10.1017/S1355771813000423>
- Rodriguez, E., George, N., Lachaux, J.-P., Martinerie, J., Renault, B., & Varela, F. J. (1999). Perception's shadow : Long-distance synchronization of human brain activity. *Nature*, 397(6718), 430-433.
<https://doi.org/10.1038/17120>
- Rodríguez-Martínez, G. (2023). Perceptual reversals and creativity : Is it possible to develop divergent thinking by modulating bistable perception? *Revista de Investigación, Desarrollo e Innovación*, 13(1), 129-144. <https://doi.org/10.19053/20278306.v13.n1.2023.16064>
- Rogowitz, B. E., & Voss, R. (1990a). *Shape perception and low-dimension fractal boundary contours* (B. E. Rogowitz & J. P. Allebach, Eds.; p. 387-394). <https://doi.org/10.1117/12.19691>
- Rogowitz, B. E., & Voss, R. F. (1990b). Shape Perception and Low-Dimension Fractal Boundary Contours. *Human Vision and Electronic Imaging, September*.

- Roy, Petitot, Pachoud, & Varela. (1999). Beyond the gap : An introduction to naturalizing phenomenology. In *Naturalizing phenomenology : Issues in contemporary phenomenology and cognitive science* (p. 1-83). Stanford University Press.
<https://cepa.info/paper.cgi?id=2034&action=add>
- Royle, J. A. (2013). *Review of : Mixed Effects Models and Extensions in Ecology with R*. 1-4.
- Rubin, E. (1915). *Synsoplevede Figurer*.
- Runco, M. A., Abdulla, A. M., Paek, S. H., Al-Jasim, F. A., & Alsuwaidi, H. N. (2016). Which Test of Divergent Thinking Is Best? *Creativity. Theories – Research - Applications*, 3(1), 4-18.
<https://doi.org/10.1515/ctra-2016-0001>
- Rutten, G.-J. (2022). Chapter 2 - Broca-Wernicke theories : A historical perspective. In A. E. Hillis & J. Fridriksson (Éds.), *Handbook of Clinical Neurology* (Vol. 185, p. 25-34). Elsevier.
<https://doi.org/10.1016/B978-0-12-823384-9.00001-3>
- Salge, J. H., Pollmann, S., & Reeder, R. R. (2021). Anomalous visual experience is linked to perceptual uncertainty and visual imagery vividness. *Psychological Research*, 85(5), 1848-1865.
<https://doi.org/10.1007/s00426-020-01364-7>
- Samaha, J., Iemi, L., Haegens, S., & Busch, N. A. (2020). Spontaneous Brain Oscillations and Perceptual Decision-Making. *Trends in Cognitive Sciences*, 24(8), 639-653.
<https://doi.org/10.1016/j.tics.2020.05.004>
- Sandsten, K. E., Nordgaard, J., & Parnas, J. (2018). [Creativity and psychosis]. *Ugeskrift for laeger*, 180(32), V02180141.
- Sanyal, S., Nag, S., Banerjee, A., Sengupta, R., & Ghosh, D. (2019). Music of brain and music on brain : A novel EEG sonification approach. *Cognitive Neurodynamics*, 13(1), 13-31.
<https://doi.org/10.1007/s11571-018-9502-4>

- Sassenberg, K., Moskowitz, G. B., Fetterman, A., & Kessler, T. (2017). Priming creativity as a strategy to increase creative performance by facilitating the activation and use of remote associations. *Journal of Experimental Social Psychology, 68*, 128-138.
<https://doi.org/10.1016/j.jesp.2016.06.010>
- Sauseng, P., Griesmayr, B., Freunberger, R., & Klimesch, W. (2010). Control mechanisms in working memory : A possible function of EEG theta oscillations. *Neuroscience & Biobehavioral Reviews, 34*(7), 1015-1022. <https://doi.org/10.1016/j.neubiorev.2009.12.006>
- Sauseng, P., Klimesch, W., Gruber, W. R., & Birbaumer, N. (2008). Cross-frequency phase synchronization : A brain mechanism of memory matching and attention. *NeuroImage, 40*(1), 308-317. <https://doi.org/10.1016/j.neuroimage.2007.11.032>
- Sawyer, K. (2011). The Cognitive Neuroscience of Creativity : A Critical Review. *Creativity Research Journal, 23*(2), 137-154. <https://doi.org/10.1080/10400419.2011.571191>
- Schartner, M. M., Carhart-Harris, R. L., Barrett, A. B., Seth, A. K., & Muthukumaraswamy, S. D. (2017). Increased spontaneous MEG signal diversity for psychoactive doses of ketamine, LSD and psilocybin. *Scientific Reports, 7*(1), 46421. <https://doi.org/10.1038/srep46421>
- Schiestl, F. P., Ayasse, M., Paulus, H. F., Löfstedt, C., Hansson, B. S., Ibarra, F., Francke, W., Taylor, R. P., & Micolich, A. P. (1999). Fractal analysis of Pollock ' s drip paintings Release from inhibition reveals the visual past Climate change related to egg-laying trends. *Nature, 399*(June), 422-423.
- Schmidhuber, J. (2010). Formal Theory of Creativity, Fun, and Intrinsic Motivation (1990–2010). *IEEE Transactions on Autonomous Mental Development, 2*(3), 230-247.
<https://doi.org/10.1109/TAMD.2010.2056368>
- Schott, G. D. (2014). Revisiting the Rorschach ink-blots : From iconography and psychology to neuroscience. *Journal of Neurology, Neurosurgery & Psychiatry, 85*(6), 699-706.
<https://doi.org/10.1136/jnnp-2013-305672>

- Schrödinger, E. (1926). An undulatory theory of the mechanics of atoms and molecules. *Physical Review*, 28(6), 1049-1070. <https://doi.org/10.1103/PhysRev.28.1049>
- Schwartzman, D. J., Bor, D., Rothen, N., & Seth, A. K. (2019). Neurophenomenology of induced and natural synaesthesia. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 374(1787), 20190030. <https://doi.org/10.1098/rstb.2019.0030>
- Sessa, B. (2008). Is it time to revisit the role of psychedelic drugs in enhancing human creativity? *Journal of Psychopharmacology*, 22(8), 821-827. <https://doi.org/10.1177/0269881108091597>
- Sethares, W. A. (1994). Adaptive tunings for musical scales. *Journal of the Acoustical Society of America*, 96(1), 10-18. <https://doi.org/10.1121/1.410471>
- Sethares, W. A. (2002). Real-time adaptive tunings using max. *International Journal of Phytoremediation*, 21(1), 347-355. <https://doi.org/10.1076/jnmr.31.4.347.14163>
- Sethares, W. A. (2005a). *Tuning, timbre, spectrum, scale* (2nd ed). Springer.
- Sethares, W. A. (2005b). Tuning, timbre, spectrum, scale. In *Springer*.
- Shahbazi Avarvand, F., Bartz, S., Andreou, C., Samek, W., Leicht, G., Mulert, C., Engel, A. K., & Nolte, G. (2018). Localizing bicoherence from EEG and MEG. *NeuroImage*, 174, 352-363. <https://doi.org/10.1016/j.neuroimage.2018.01.044>
- Shen, W., Yuan, Y., Liu, C., & Luo, J. (2016). In search of the « Aha! » experience : Elucidating the emotionality of insight problem-solving. *British Journal of Psychology*, 107(2), 281-298. <https://doi.org/10.1111/bjop.12142>
- Shew, W. L., & Plenz, D. (2013). The Functional Benefits of Criticality in the Cortex. *The Neuroscientist*, 19(1), 88-100. <https://doi.org/10.1177/1073858412445487>
- Shi, L., Beaty, R. E., Chen, Q., Sun, J., Wei, D., Yang, W., & Qiu, J. (2019). Brain Entropy is Associated with Divergent Thinking. *Cerebral Cortex*, bhz120. <https://doi.org/10.1093/cercor/bhz120>

- Shimizu, Y., Umeda, M., Mano, H., Aoki, I., Higuchi, T., & Tanaka, C. (2007). Neuronal response to Shepard's tones. An auditory fMRI study using multifractal analysis. *Brain Research*, *1186*, 113-123. <https://doi.org/10.1016/j.brainres.2007.09.097>
- Shine, J. M., Halliday, G. M., Naismith, S. L., & Lewis, S. J. G. (2011). Visual misperceptions and hallucinations in Parkinson's disease : Dysfunction of attentional control networks? *Movement Disorders*, *26*(12), 2154-2159. <https://doi.org/10.1002/mds.23896>
- Shine, J. M., Muller, A. J., O'Callaghan, C., Hornberger, M., Halliday, G. M., & Lewis, S. J. (2015). Abnormal connectivity between the default mode and the visual system underlies the manifestation of visual hallucinations in Parkinson's disease : A task-based fMRI study. *Npj Parkinson's Disease*, *1*(1), 15003. <https://doi.org/10.1038/npjparkd.2015.3>
- Shukla, B., & Bidelman, G. M. (2021). Enhanced brainstem phase-locking in low-level noise reveals stochastic resonance in the frequency-following response (FFR). *Brain Research*, *1771*(April), 147643. <https://doi.org/10.1016/j.brainres.2021.147643>
- Simoncelli, E. P., & Olshausen, B. A. (2001). Natural image statistics and neural representation. *Annual Review in Neurosciences*.
- Simonton, D. K. (2010a). Creative thought as blind-variation and selective-retention : Combinatorial models of exceptional creativity. *Physics of Life Reviews*, *7*(2), 156-179. <https://doi.org/10.1016/j.plrev.2010.02.002>
- Simonton, D. K. (2010b). Creative thought as blind-variation and selective-retention : Combinatorial models of exceptional creativity. *Physics of Life Reviews*, *7*(2), 156-179. <https://doi.org/10.1016/j.plrev.2010.02.002>
- Simonton, D. K. (2011). Creativity and discovery as blind variation and selective retention : Multiple-variant definition and blind-sighted integration. *Psychology of Aesthetics, Creativity, and the Arts*, *5*(3), 222-228. <https://doi.org/10.1037/a0023144>

- Simonton, D. K. (2015a). On Praising Convergent Thinking : Creativity as Blind Variation and Selective Retention. *Creativity Research Journal*, 27(3), 262-270.
<https://doi.org/10.1080/10400419.2015.1063877>
- Simonton, D. K. (2015b). On Praising Convergent Thinking : Creativity as Blind Variation and Selective Retention. *Creativity Research Journal*, 27(3), 262-270.
<https://doi.org/10.1080/10400419.2015.1063877>
- Singleton, S. P., Luppi, A. I., Carhart-Harris, R. L., Cruzat, J., Deco, G., Kringelbach, M. L., & Stamatakis, E. A. (2021). *LSD flattens the brain's energy landscape : Evidence from receptor-informed network control theory*.
- Singleton, S. P., Luppi, A. I., Carhart-Harris, R. L., Cruzat, J., Roseman, L., Nutt, D. J., Deco, G., Kringelbach, M. L., Stamatakis, E. A., & Kuceyeski, A. (2022). Receptor-informed network control theory links LSD and psilocybin to a flattening of the brain's control energy landscape. *Nature Communications*, 13(1), 5812. <https://doi.org/10.1038/s41467-022-33578-1>
- Skiteva, L., Aleksandr, T., Vadim, U., Denis, M., & Boris, M. V. (2016). MEG Data Analysis Using the Empirical Mode Decomposition Method. *Biologically inspired cognitive architectures (BICA) for young scientists*, 135-140. <https://doi.org/10.1007/978-3-319-32554-5>
- Smailes, D., Burdis, E., Gregoriou, C., Fenton, B., & Dudley, R. (2021). *Pareidolia-proneness, reality discrimination errors, and visual hallucination-like experiences in a non-clinical sample*.
- Smalley, D. (1997). Spectromorphology : Explaining sound-shapes. *Organised Sound*, 2(2), 107-126.
<https://doi.org/10.1017/S1355771897009059>
- Smyth, T., & Smith, J. O. (2001). *APPLICATIONS OF BIOACOUSTICS IN PHYSICAL MODELING AND THE CREATION OF NEW MUSICAL INSTRUMENTS*.

- Sowden, P. T., Pringle, A., & Gabora, L. (2015). The shifting sands of creative thinking : Connections to dual-process theory. *Thinking & Reasoning*, *21*(1), 40-60.
<https://doi.org/10.1080/13546783.2014.885464>
- Spehar, B., Clifford, C. W. G., Newell, B. R., & Taylor, R. P. (2003). Universal aesthetic of fractals. *Computers & Graphics*, *27*(5), 813-820. [https://doi.org/10.1016/S0097-8493\(03\)00154-7](https://doi.org/10.1016/S0097-8493(03)00154-7)
- Spehar, B., Walker, N., & Taylor, R. P. (2016). Taxonomy of individual variations in aesthetic responses to fractal patterns. *Frontiers in Human Neuroscience*, *10*(July), 1-18.
<https://doi.org/10.3389/fnhum.2016.00350>
- Sripriya, N., & Nagarajan, T. (2013). Pitch estimation using harmonic product spectrum derived from DCT. *IEEE Region 10 Annual International Conference, Proceedings/TENCON*.
<https://doi.org/10.1109/TENCON.2013.6718976>
- Stam, C. J., & van Straaten, E. C. W. (2012). The organization of physiological brain networks. *Clinical Neurophysiology*, *123*(6), 1067-1087. <https://doi.org/10.1016/j.clinph.2012.01.011>
- Steinbeis, N., & Koelsch, S. (2008a). Comparing the Processing of Music and Language Meaning Using EEG and fMRI Provides Evidence for Similar and Distinct Neural Representations. *PLoS ONE*, *3*(5), e2226. <https://doi.org/10.1371/journal.pone.0002226>
- Steinbeis, N., & Koelsch, S. (2008b). Shared Neural Resources between Music and Language Indicate Semantic Processing of Musical Tension-Resolution Patterns. *Cerebral Cortex*, *18*(5), 1169-1178.
<https://doi.org/10.1093/cercor/bhm149>
- Sternberg, R. J., & Lubart, T. I. (1998). The Concept of Creativity : Prospects and Paradigms. In R. J. Sternberg (Éd.), *Handbook of Creativity* (p. 3-15). Cambridge University Press.
<https://doi.org/10.1017/CBO9780511807916.003>

- Stoliker, D., Novelli, L., Vollenweider, F. X., Egan, G. F., Preller, K. H., & Razi, A. (2023). Effective Connectivity of Functionally Anticorrelated Networks Under Lysergic Acid Diethylamide. *Biological Psychiatry*, 93(3), 224-232. <https://doi.org/10.1016/j.biopsych.2022.07.013>
- Stoll, E. A. (2024). A thermodynamical model of non-deterministic computation in cortical neural networks. *Physical Biology*, 21(1), 016003. <https://doi.org/10.1088/1478-3975/ad0f2d>
- Stupacher, J., Wood, G., & Witte, M. (2017). Neural Entrainment to Polyrhythms : A Comparison of Musicians and Non-musicians. *Frontiers in Neuroscience*, 11. <https://doi.org/10.3389/fnins.2017.00208>
- Summa, M. (2017). Toward a transcendental account of creativity. Kant and Merleau-Ponty on the creative power of judgment and creativity as institution. *Continental Philosophy Review*, 50(1), 105-126. <https://doi.org/10.1007/s11007-016-9391-3>
- Suzuki, K., Roseboom, W., Schwartzman, D. J., & Seth, A. K. (2017). A Deep-Dream Virtual Reality Platform for Studying Altered Perceptual Phenomenology. *Scientific Reports*, 7(1), 15982. <https://doi.org/10.1038/s41598-017-16316-2>
- Tabatabaeian, S., & Jennings, C. (2023). Dynamic attentional mechanisms of creative cognition. *Philosophy and the Mind Sciences*, 4. <https://doi.org/10.33735/phimisci.2023.10020>
- Tagliazucchi, E., Carhart-Harris, R., Leech, R., Nutt, D., & Chialvo, D. R. (2014). Enhanced repertoire of brain dynamical states during the psychedelic experience. *Human Brain Mapping*, 35(11), 5442-5456. <https://doi.org/10.1002/hbm.22562>
- Tallon-Baudry, C., & Bertrand, O. (1999). Activity in humans and its role in object representation. *Trends in Cognitive Sciences*, 3(4).
- Taylor, R. P., Martin, T. P., Montgomery, R. D., Smith, J. H., Micolich, A. P., Boydston, C., Scannell, B. C., Fairbanks, M. S., & Spehar, B. (2017a). Seeing shapes in seemingly random spatial patterns :

- Fractal analysis of Rorschach inkblots. *PLOS ONE*, 12(2), e0171289.
<https://doi.org/10.1371/journal.pone.0171289>
- Taylor, R. P., Martin, T. P., Montgomery, R. D., Smith, J. H., Micolich, A. P., Boydston, C., Scannell, B. C., Fairbanks, M. S., & Spehar, B. (2017b). Seeing shapes in seemingly random spatial patterns : Fractal analysis of Rorschach inkblots. *PLoS ONE*, 12(2), 1-17.
<https://doi.org/10.1371/journal.pone.0171289>
- Taylor, R. P., & Spehar, B. (2016). Fractal Fluency : An Intimate Relationship Between the Brain and Processing of Fractal Stimuli. *Fractal Geometry and Nonlinear Analysis in Medicine and Biology*, 2(3). <https://doi.org/10.15761/fgnamb.1000138>
- Taylor, R. P., Spehar, B., Wise, J. A., Clifford, C. W. G., Newell, B. R., Hagerhall, C. M., Purcell, T., & Martin, T. P. (2005). Perceptual and physiological responses to the visual complexity of fractal patterns. *Nonlinear Dynamics, Psychology, and Life Sciences*, 9(1), 89-114.
- Temperley, D. (2004). Bayesian models of musical structure and cognition. *Musicae Scientiae*, 8(2), 175-205. <https://doi.org/10.1177/102986490400800204>
- Teplan, M. (2002). Fundamentals of EEG measurement. *Measurement Science Review*, 2.
- Terhardt, E. (1991). Music Perception and Sensory Information Acquisition : Relationships and Low-Level Analogies. *Music Perception*, 8(3), 217-239. <https://doi.org/10.2307/40285500>
- Thaler, S. L. (2016). Cycles of insanity and creativity within contemplative neural systems. *Medical Hypotheses*, 94, 138-147. <https://doi.org/10.1016/j.mehy.2016.07.010>
- Timmermann, C., Roseman, L., Haridas, S., Rosas, F. E., Luan, L., Kettner, H., Martell, J., Erritzoe, D., Tagliazucchi, E., Pallavicini, C., Girn, M., Alamia, A., Leech, R., Nutt, D. J., & Carhart-Harris, R. L. (2023). Human brain effects of DMT assessed via EEG-fMRI. *Proceedings of the National Academy of Sciences*, 120(13), e2218949120. <https://doi.org/10.1073/pnas.2218949120>

- Timmermann, C., Roseman, L., Schartner, M., Milliere, R., Williams, L. T. J., Erritzoe, D., Muthukumaraswamy, S., Ashton, M., Bendrioua, A., Kaur, O., Turton, S., Nour, M. M., Day, C. M., Leech, R., Nutt, D. J., & Carhart-Harris, R. L. (2019). Neural correlates of the DMT experience assessed with multivariate EEG. *Scientific Reports*, *9*(1), 16324. <https://doi.org/10.1038/s41598-019-51974-4>
- Todd, P. M., Hills, T. T., & Robbins, T. W. (2012). *Cognitive Search : Evolution, Algorithms, and the Brain*. MIT Press.
- Tolhurst, D. J., Tadmor, Y., & Chao, T. (1992). Amplitude spectra of natural images. *Ophthalmic and Physiological Optics*, *12*(2), 229-232. <https://doi.org/10.1111/j.1475-1313.1992.tb00296.x>
- Torrance, E. P. (1962). Non-Test Ways of Identifying the Creatively Gifted. *Gifted Child Quarterly*, *6*(3), 71-75. <https://doi.org/10.1177/001698626200600301>
- Torrance, E. P. (1966). *Torrance Tests of Creative Thinking* [jeu de données]. <https://doi.org/10.1037/t05532-000>
- Toussaint, G. (2005). *The Euclidean Algorithm Generates Traditional Musical Rhythms*. 47-56. <https://archive.bridgesmathart.org/2005/bridges2005-47.html#gsc.tab=0>
- Tramo, M. J., Cariani, P. A., Delgutte, B., & Braida, L. D. (2001). Neurobiological foundations for the theory of harmony in Western tonal music. *Annals of the New York Academy of Sciences*, *930*, 92-116. <https://doi.org/10.1111/j.1749-6632.2001.tb05727.x>
- Treffert, D. A. (2009). The savant syndrome : An extraordinary condition. A synopsis: past, present, future. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1522), 1351-1357. <https://doi.org/10.1098/rstb.2008.0326>
- Ueno, K., Takahashi, T., Takahashi, K., Mizukami, K., Tanaka, Y., & Wada, Y. (2015). Neurophysiological basis of creativity in healthy elderly people : A multiscale entropy approach. *Clinical Neurophysiology*, *126*(3), 524-531. <https://doi.org/10.1016/j.clinph.2014.06.032>

- Uusberg, A., Thiruchselvam, R., & Gross, J. J. (2014). Using distraction to regulate emotion : Insights from EEG theta dynamics. *International Journal of Psychophysiology*, 91(3), 254-260.
<https://doi.org/10.1016/j.ijpsycho.2014.01.006>
- Väljamäe, A., Holland, S., Marimon, X., Benitez, R., Mealla, S., & Oliveira, A. (2013). A Review of Real Time EEG sonification research. *International Conference on Auditory Display 2013 (ICAD 2013)*.
- Van De Cruys, S., & Wagemans, J. (2011). Putting Reward in Art : A Tentative Prediction Error Account of Visual Art. *I-Perception*, 2(9), 1035-1062. <https://doi.org/10.1068/i0466aap>
- Van Eyghen, H. (2023). Psychedelics and the Entropic Brain Beyond the Self. *The International Journal for the Psychology of Religion*, 1-17. <https://doi.org/10.1080/10508619.2023.2192078>
- Varela, F. J. (1999). The specious present : A neurophenomenology of time consciousness. In *Naturalizing phenomenology : Issues in contemporary phenomenology and cognitive science* (p. 266-314). Stanford University Press.
- Varela, F. J., Rosch, E., & Thompson, E. (1991). *The Embodied Mind*. The MIT Press.
<https://doi.org/10.7551/mitpress/6730.001.0001>
- Varela, F. J., Thompson, E., & Rosch, E. (2017). *The Embodied Mind, revised edition : Cognitive Science and Human Experience*. MIT Press.
- Varela, F., Lachaux, J.-P., Rodriguez, E., & Martinerie, J. (2001). The brainweb : Phase synchronization and large-scale integration. *Nature Reviews Neuroscience*, 2(4), 229-239.
<https://doi.org/10.1038/35067550>
- Vercammen, A., De Haan, E. H. F., & Aleman, A. (2008). Hearing a voice in the noise : Auditory hallucinations and speech perception. *Psychological Medicine*, 38(8), 1177-1184.
<https://doi.org/10.1017/S0033291707002437>
- Vetter, P., Smith, F. W., & Muckli, L. (2014). Decoding Sound and Imagery Content in Early Visual Cortex. *Current Biology*, 24(11), 1256-1262. <https://doi.org/10.1016/j.cub.2014.04.020>

- Viengkham, C., & Spehar, B. (2018). Preference for fractal-scaling properties across synthetic noise images and artworks. *Frontiers in Psychology, 9*(AUG), 1-19.
<https://doi.org/10.3389/fpsyg.2018.01439>
- Viol, A., Palhano-Fontes, F., Onias, H., De Araujo, D. B., & Viswanathan, G. M. (2017). Shannon entropy of brain functional complex networks under the influence of the psychedelic Ayahuasca. *Scientific Reports, 7*(1), 7388. <https://doi.org/10.1038/s41598-017-06854-0>
- Viol, A., Palhano-Fontes, F., Onias, H., De Araujo, D., Hövel, P., & Viswanathan, G. (2019). Characterizing Complex Networks Using Entropy-Degree Diagrams : Unveiling Changes in Functional Brain Connectivity Induced by Ayahuasca. *Entropy, 21*(2), 128. <https://doi.org/10.3390/e21020128>
- Vollenweider, F. X., & Geyer, M. A. (2001). A systems model of altered consciousness : Integrating natural and drug-induced psychoses. *Brain Research Bulletin, 56*(5), 495-507.
[https://doi.org/10.1016/S0361-9230\(01\)00646-3](https://doi.org/10.1016/S0361-9230(01)00646-3)
- Vuust, P., Gebauer, L., & Witek, M. A. G. (2014). Neural underpinnings of music : The polyrhythmic brain. In *Neurobiology of interval timing* (p. 339--356).
- Vuust, P., & Witek, M. A. G. (2014). Rhythmic complexity and predictive coding : A novel approach to modeling rhythm and meter perception in music. *Frontiers in Psychology, 5*.
<https://doi.org/10.3389/fpsyg.2014.01111>
- Vygotsky, L. S. (2004). *Imagination and Creativity in Childhood*.
- Vyshedskiy, A. (2019). *Neuroscience of imagination and implications for human evolution* [Preprint]. PsyArXiv. <https://doi.org/10.31234/osf.io/skxwc>
- Wagemans, J., Elder, J. H., Kubovy, M., Palmer, S. E., Peterson, M. A., Singh, M., & von der Heydt, R. (2012). A century of Gestalt psychology in visual perception : I. Perceptual grouping and figure-ground organization. *Psychological Bulletin, 138*(6), 1172-1217.
<https://doi.org/10.1037/a0029333>

- Wagemans, J., Feldman, J., Gepshtein, S., Kimchi, R., Pomerantz, J. R., van der Helm, P. A., & van Leeuwen, C. (2012). A century of Gestalt psychology in visual perception : II. Conceptual and theoretical foundations. *Psychological Bulletin*, *138*, 1218-1252.
<https://doi.org/10.1037/a0029334>
- Wang, Z., Liu, J., Zhong, N., Qin, Y., Zhou, H., & Li, K. (2012). Changes in the brain intrinsic organization in both on-task state and post-task resting state. *NeuroImage*, *62*(1), 394-407.
<https://doi.org/10.1016/j.neuroimage.2012.04.051>
- Ward, T. B., Smith, S. M., & Finke, R. A. (1999). A Creative Cognition. In *Handbook of creativity*.
<https://doi.org/10.7312/columbia/9780231178426.003.0007>
- Wardle, S. G., Taubert, J., Teichmann, L., & Baker, C. I. (2020). Rapid and dynamic processing of face pareidolia in the human brain. *Nature Communications*, *11*(1), 1-14.
<https://doi.org/10.1038/s41467-020-18325-8>
- Waschke, L., Donoghue, T., Fiedler, L., Smith, S., Garrett, D. D., Voytek, B., & Obleser, J. (2021). Modality-specific tracking of attention and sensory statistics in the human electrophysiological spectral exponent. *eLife*, *10*, e70068. <https://doi.org/10.7554/eLife.70068>
- Waschke, L., Donoghue, T., Smith, S., Voytek, B., & Obleser, J. (2019). Aperiodic EEG activity tracks 1/f stimulus characteristics and the allocation of cognitive resources. *2019 Conference on Cognitive Computational Neuroscience*. 2019 Conference on Cognitive Computational Neuroscience, Berlin, Germany. <https://doi.org/10.32470/CCN.2019.1111-0>
- Wei, Q., Wang, Y., Gao, X., & Gao, S. (2007). Amplitude and phase coupling measures for feature extraction in an EEG-based brain-computer interface. *Journal of Neural Engineering*, *4*(2), 120-129. <https://doi.org/10.1088/1741-2560/4/2/012>
- Weisberg, Robert. W. (2006). Creativity : Understanding innovation in problem solving, science, invention, and the arts. In *John Wiley & Sons*.

- [https://www.researchgate.net/publication/269107473_What_is_governance/link/548173090cf22525dcb61443/download%0Ahttp://www.econ.upf.edu/\\$\sim\\$reynal/Civilwars_12December2010.pdf%0Ahttps://think-asia.org/handle/11540/8282%0Ahttps://www.jstor.org/stable/41857625](https://www.researchgate.net/publication/269107473_What_is_governance/link/548173090cf22525dcb61443/download%0Ahttp://www.econ.upf.edu/\simreynal/Civilwars_12December2010.pdf%0Ahttps://think-asia.org/handle/11540/8282%0Ahttps://www.jstor.org/stable/41857625)
- Werbock, B. J. (2011). Inner Octaves and Eastern Music. *Gurdjieff International*.
- Wernery, J. (2013). Bistable Perception of the Necker Cube in the Context of Cognition & Personality. *Dissertation ETH Zurich, 21214, 1-154*.
- Wertheimer, M. (2017). *Max Wertheimer and Gestalt Theory*. Routledge.
<https://doi.org/10.4324/9780203783573>
- Wiggins, G. A. (2006). Searching for computational creativity. *New Generation Computing, 24*(3), 209-222. <https://doi.org/10.1007/BF03037332>
- Williams, J., Carr, M., & Blagrove, M. (2021). Sensory Processing Sensitivity : Associations with the Detection of Real Degraded Stimuli, and Reporting of Illusory Stimuli and Paranormal Experiences. *Personality and Individual Differences*.
- Witt, J. K., & Riley, M. A. (2014). Discovering your inner Gibson : Reconciling action-specific and ecological approaches to perception–action. *Psychonomic Bulletin & Review, 21*(6), 1353-1370.
<https://doi.org/10.3758/s13423-014-0623-4>
- Witrock, M. C. (1992). Generative Learning Processes of the Brain. *Educational Psychologist, 27*(4), 531-541. https://doi.org/10.1207/s15326985ep2704_8
- Woertz, M., Pfurtscheller, G., & Klimesch, W. (2004). Alpha power dependent light stimulation : Dynamics of event-related (de)synchronization in human electroencephalogram. *Cognitive Brain Research, 20*(2), 256-260. <https://doi.org/10.1016/j.cogbrainres.2004.03.014>
- Wotruba, D., Michels, L., Buechler, R., Metzler, S., Theodoridou, A., Gerstenberg, M., Walitza, S., Kollias, S., Rössler, W., & Heekeren, K. (2014). Aberrant Coupling Within and Across the Default Mode,

- Task-Positive, and Salience Network in Subjects at Risk for Psychosis. *Schizophrenia Bulletin*, 40(5), 1095-1104. <https://doi.org/10.1093/schbul/sbt161>
- Wu, D., Li, C. Y., & Yao, D. Z. (2009). Scale-free music of the brain. *PLoS ONE*, 4(6), 4-11. <https://doi.org/10.1371/journal.pone.0005915>
- Wu, X., Gu, X., & Zhang, H. (2019). The Facilitative Effects of Ambiguous Figures on Creative Solution. *The Journal of Creative Behavior*, 53(1), 44-51. <https://doi.org/10.1002/jocb.161>
- Wu, X., Yang, W., Tong, D., Sun, J., Chen, Q., Wei, D., Zhang, Q., Zhang, M., & Qiu, J. (2015). A meta-analysis of neuroimaging studies on divergent thinking using activation likelihood estimation. *Human Brain Mapping*, 36(7), 2703-2718. <https://doi.org/10.1002/hbm.22801>
- Xu, J., Li, H., & Zhou, S. (2015). An Overview of Deep Generative Models. *IETE Technical Review*, 32(2), 131-139. <https://doi.org/10.1080/02564602.2014.987328>
- Yokoi, K., Nishio, Y., Uchiyama, M., Shimomura, T., Iizuka, O., & Mori, E. (2014). Hallucinators find meaning in noises : Pareidolic illusions in dementia with Lewy bodies. *Neuropsychologia*, 56, 245-254. <https://doi.org/10.1016/j.neuropsychologia.2014.01.017>
- Yoshii, K., & Goto, M. (2012). A Nonparametric Bayesian Multipitch Analyzer Based on Infinite Latent Harmonic Allocation. *IEEE Transactions on Audio, Speech and Language Processing*, 20(3), 717-730. <https://doi.org/10.1109/TASL.2011.2164530>
- Young, A., Hunt, T., & Ericson, M. (2022). The Slowest Shared Resonance : A Review of Electromagnetic Field Oscillations Between Central and Peripheral Nervous Systems. *Frontiers in Human Neuroscience*, 15, 796455. <https://doi.org/10.3389/fnhum.2021.796455>
- Zabelina, D. L., & Robinson, M. D. (2010). Creativity as flexible cognitive control. *Psychology of Aesthetics, Creativity, and the Arts*, 4(3), 136-143. <https://doi.org/10.1037/a0017379>

- Zabelina, D., Saporta, A., & Beeman, M. (2016). Flexible or leaky attention in creative people? Distinct patterns of attention for different types of creative thinking. *Memory & Cognition*, 44(3), 488-498. <https://doi.org/10.3758/s13421-015-0569-4>
- Zander, T. O., & Kothe, C. (2011). Towards passive brain-computer interfaces : Applying brain-computer interface technology to human-machine systems in general. *Journal of Neural Engineering*, 8(2). <https://doi.org/10.1088/1741-2560/8/2/025005>
- Zatorre, R. J., Delhommeau, K., & Zarate, J. M. (2012). Modulation of Auditory Cortex Response to Pitch Variation Following Training with Microtonal Melodies. *Frontiers in Psychology*, 3. <https://doi.org/10.3389/fpsyg.2012.00544>
- Zhang, Z., Wu, J., Li, Q., Huang, Z., Traer, J., McDermott, J. H., Tenenbaum, J. B., & Freeman, W. T. (2017). Generative Modeling of Audible Shapes for Object Perception. *2017 IEEE International Conference on Computer Vision (ICCV)*, 1260-1269. <https://doi.org/10.1109/ICCV.2017.141>
- Zhao, L., & He, Y. (2013). Power Spectrum Estimation of the Welch Method Based on Imagery EEG. *Applied Mechanics and Materials*, 278-280, 1260-1264. <https://doi.org/10.4028/www.scientific.net/AMM.278-280.1260>
- Zhong, C.-B., Dijksterhuis, A., & Galinsky, A. D. (2008). The Merits of Unconscious Thought in Creativity. *Psychological Science*, 19(9), 912-918. <https://doi.org/10.1111/j.1467-9280.2008.02176.x>
- Zhu, W., Chen, Q., Xia, L., Beaty, R. E., Yang, W., Tian, F., Sun, J., Cao, G., Zhang, Q., Chen, X., & Qiu, J. (2017). Common and distinct brain networks underlying verbal and visual creativity : Brain Networks Underlying Verbal and Visual Creativity. *Human Brain Mapping*, 38(4), 2094-2111. <https://doi.org/10.1002/hbm.23507>

Appendices

SUPPLEMENTARY MATERIAL (CHAPTER 1)

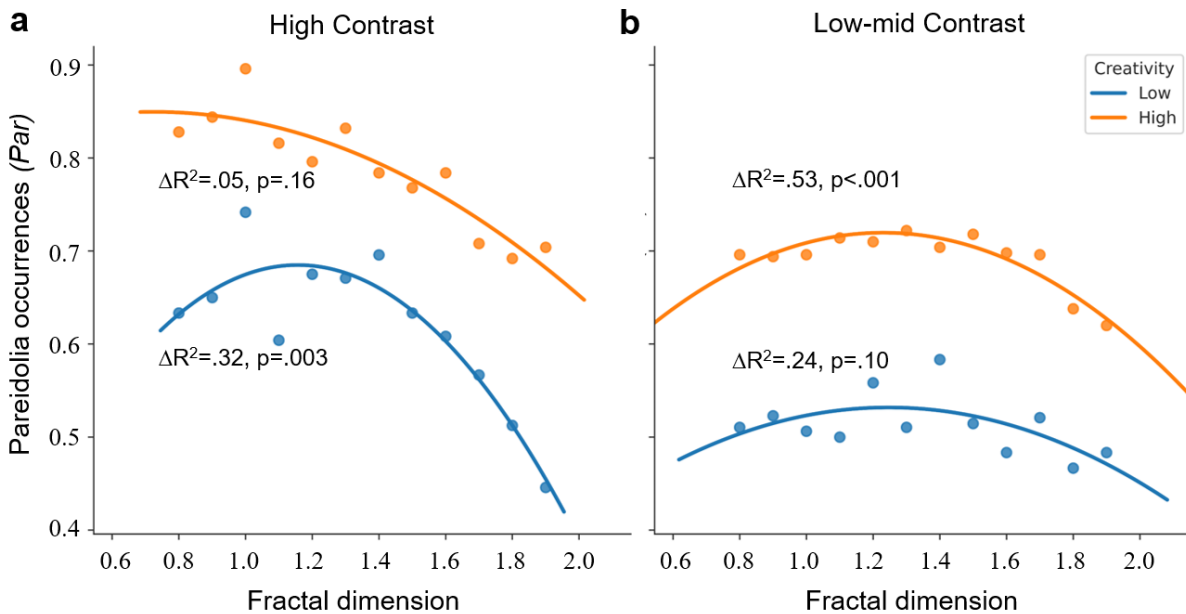


Figure. S2.1. Pareidolia for high- and low- creatives across fractal dimensions Related to Figure 2.5. To understand more precisely how creativity, fractal dimension and contrast interact in predicting pareidolia occurrences, we first divided subjects in low- and high-creatives using a median split, and then conducted regression analyses between FD and pareidolia for low-to-mid contrast and high-contrast images. For images with high contrast, we show significant quadratic regression for low-creatives ($\Delta R^2=.32, p=.003$), while for high-creatives, only linear regression significantly predicts the occurrence of pareidolia ($\Delta R^2=.05, p=.16$). For images with low to-mid-contrast, we report a significant quadratic regression only for the high-creative group ($\Delta R^2=.53, p<.001$). This figure illustrates the tendency of low-creative individuals to experience pareidolia more often at mid-FDs (around 1.3). **(a)** High-contrast images. **(b)** Low-mid-contrast images. ΔR^2 corresponds to the change in the coefficient of determination when going from linear to quadratic regression model.

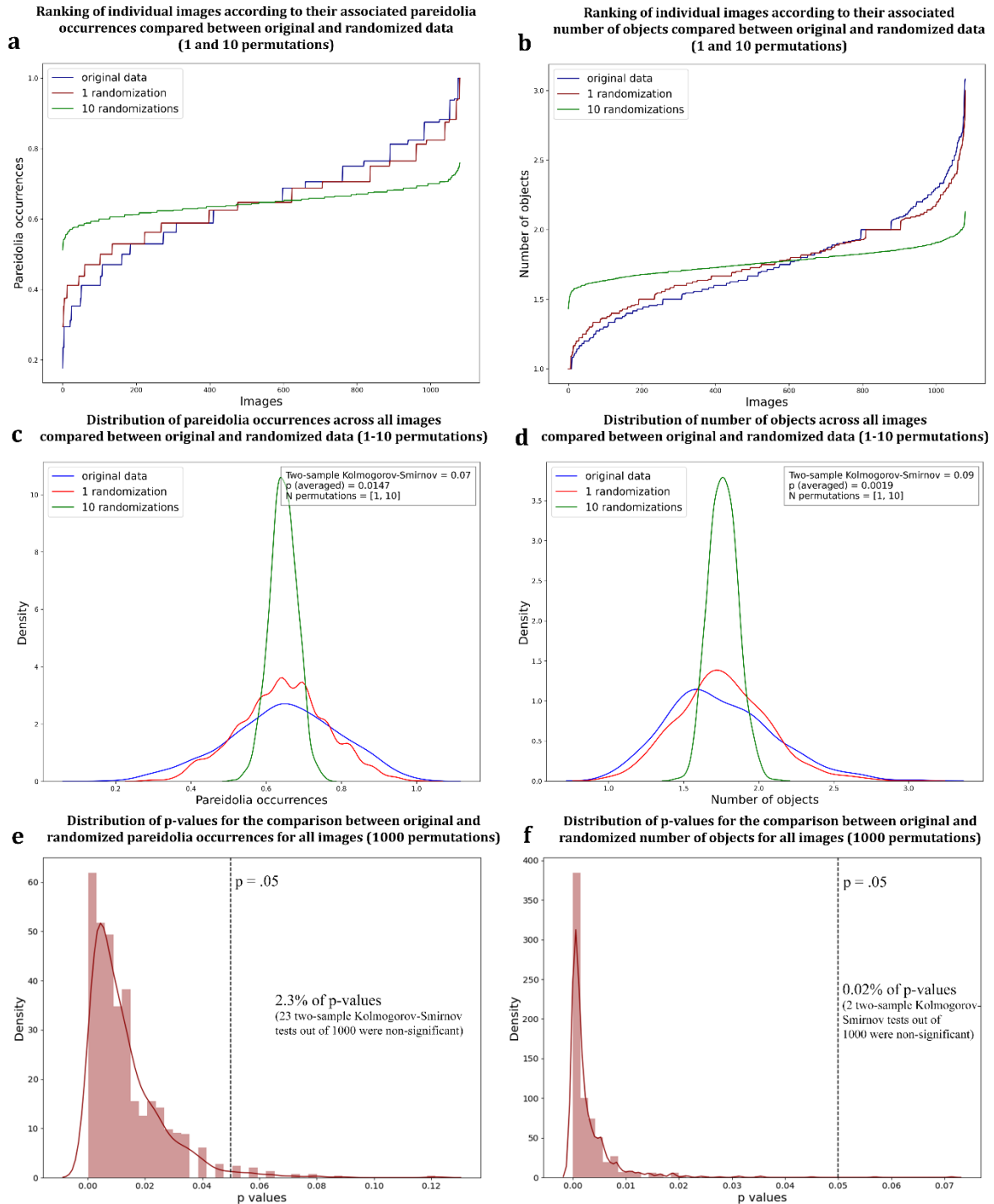


Figure S2.2. Image-based analysis of pareidolia occurrence (left column) and frequency of occurrence (right column) across subjects. Related to Figure 2.2. This image-based analysis of reported pareidolia was conducted to check whether there was some evidence for consistency across participants in their responses to identical stimuli. If the responses of the participants (i.e. pareidolia occurrence and number of percepts) were random and unrelated to pareidolia occurrence, we'd expect the mean pareidolia responses for the stimuli to be similar across stimuli. First, we computed the mean value of pareidolia occurrence and number of percepts reported for each single image. We then computed new

means for the same variable but this time after randomly shuffling the provided responses across all stimuli (as a realization of a mean of random responses for each stimulus). We also computed the results using the mean of 10 such randomizations. If the participants' responses were driven by pareidolia, rather than random behavior, we'd expect that -across the group- some images will elicit more pareidolia than others. a, b. Ranking of individual images (360 x 3 contrast levels) by their mean pareidolia scores across subjects. The original data contain more images associated with very rare and very frequent pareidolia than distribution obtained by randomized data across stimuli and subjects. c, d. The distribution plot for the original data also shows longer tails than the surrogate data. e, f. differences between the distribution of the original pareidolia response data and 1000 randomized sets of responses using two-sample Kolmogorov-Smirnov tests. Both for pareidolia occurrence and for the number of objects variables, we found that the response distributions across subjects were significantly different from the distributions of random behavioral responses. These results indicate that the distribution of the original data significantly differs from that of randomly generated behavioral responses.

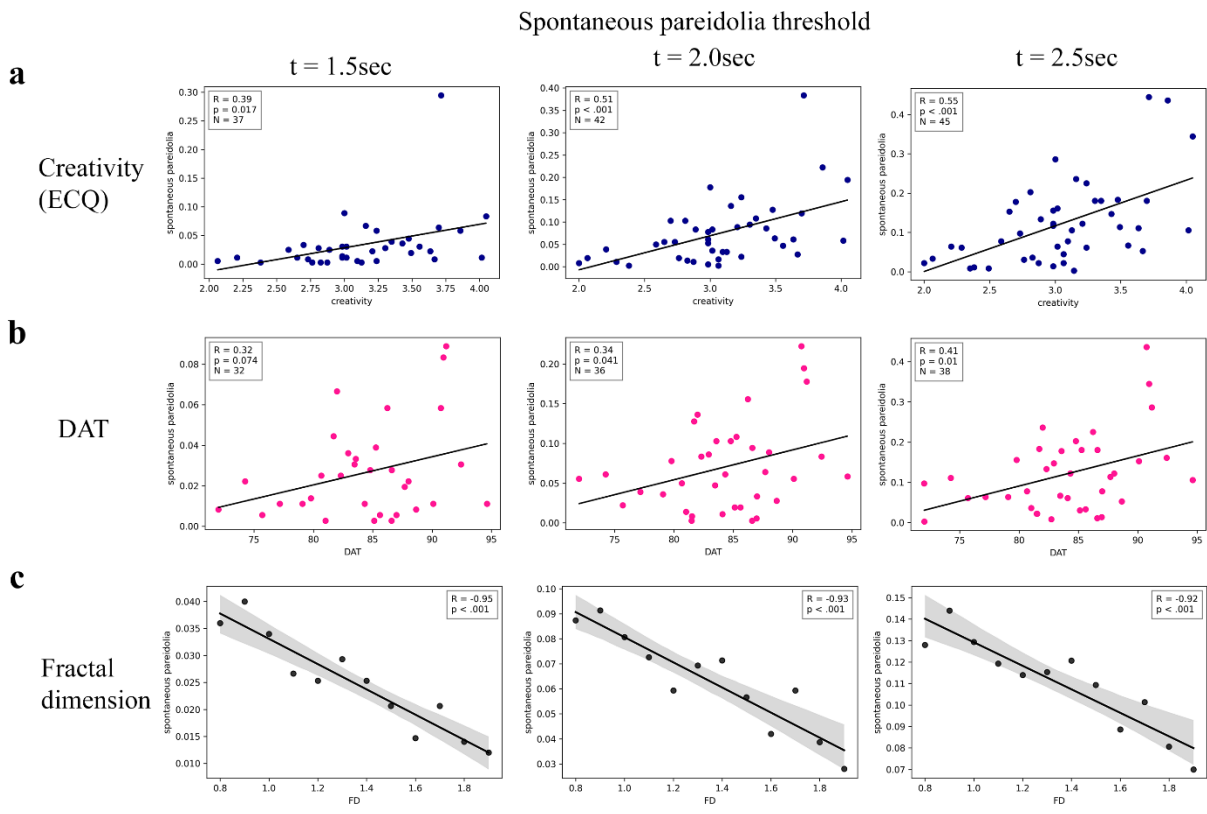


Figure S2.3. Comparing correlations between spontaneous pareidolia, creativity questionnaire and fractal dimension for different threshold values. Related to Figure 2.2. We introduced a measure for the concept of “spontaneous pareidolia” to capture the quick emergence of pareidolic percepts that “pop up” and distinguish them from later events that result from an active and deliberate search in the ambiguous stimulus. This required a temporal threshold to define what we consider to be a quick/spontaneous emergence. We tested spontaneous pareidolia at three different thresholds (1.5, 2 and 2.5 sec). **(a)** Spearman correlations between self-reported creativity (ECQ) and spontaneous pareidolia across thresholds. **(b)** Spearman correlations between divergent association task (DAT) and spontaneous pareidolia across thresholds. **(c)** Spearman correlations between fractal dimension of stimuli and spontaneous pareidolia across thresholds. From this investigation, 2 seconds seems to be a reliable threshold to adopt.

Distribution plots for the six variables used in the correlation matrix

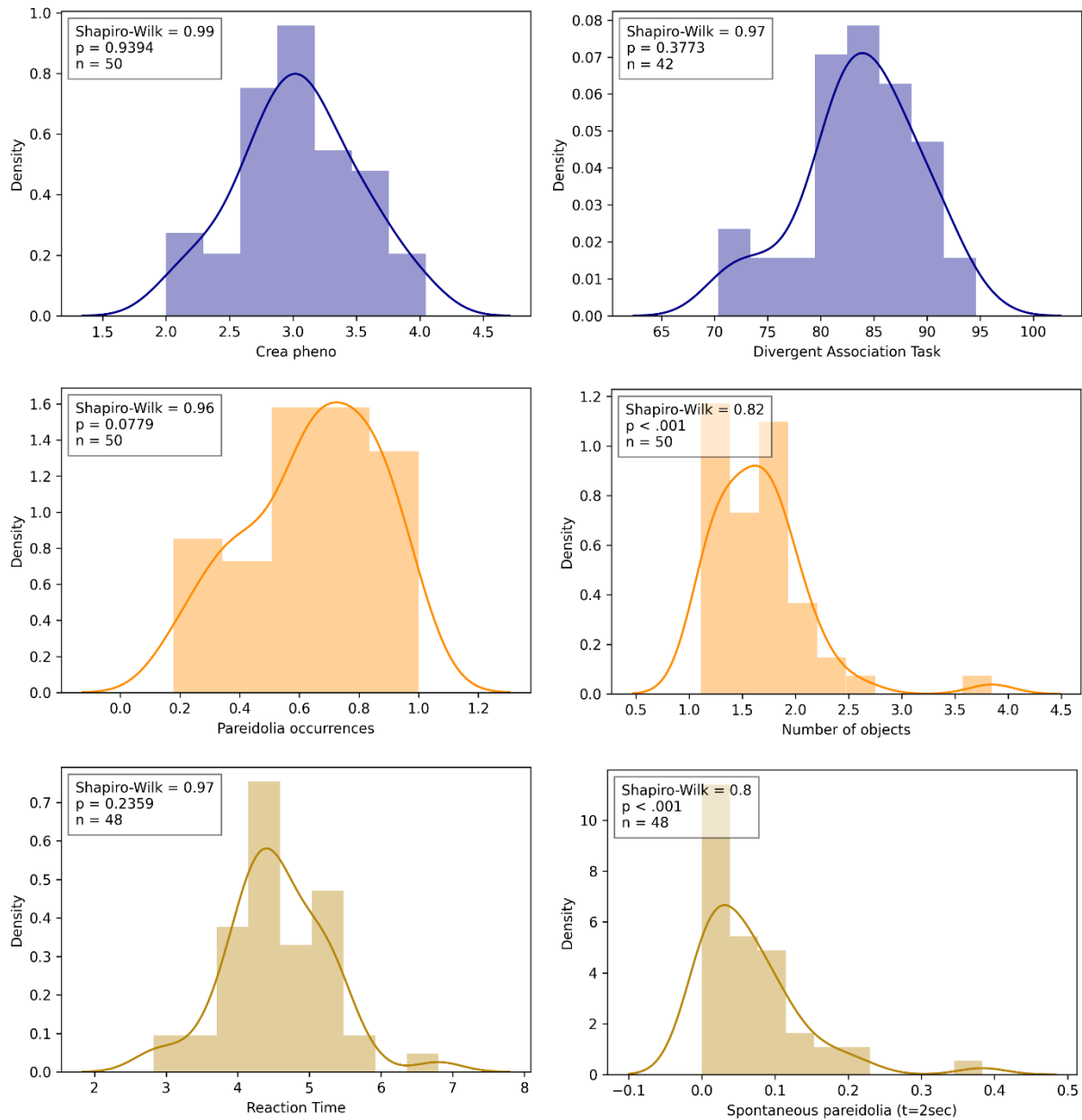


Figure S2.4. Distribution plots for the six variables in the correlation matrix with Shapiro-Wilk normality tests. Related to Figure 3.

| Fixed effects | Estimate | Std. Error | z value | p-value |
|------------------------------|----------|------------|---------|------------|
| (Intercept) | 1.35 | 0.17 | 7.86 | < 0.001*** |
| <i>FD</i> | 0.66 | 0.25 | 2.70 | 0.007** |
| <i>FD</i> ² | -0.92 | 0.23 | -3.98 | < 0.001*** |
| Contrast | -0.57 | 0.04 | -13.30 | < 0.001*** |
| DAT | 0.57 | 0.16 | 3.68 | < 0.001*** |
| <i>FD</i> * DAT | 0.32 | 0.25 | 1.28 | 0.20 |
| <i>FD</i> ² * DAT | -0.45 | 0.23 | -2.01 | 0.04* |

Table S2.1. Moderation effect of FD on Divergent Thinking in predicting Pareidolia (Par). Related to Figure 2,4D. Number of participants = 42, number of trials = 360, total N = 15,120. *: $p < .05$; **: $p < .01$; ***: $p < .001$. GLMM built to predict pareidolia occurrences from Divergent Thinking (*DAT*), fractal dimension (*FD*) and contrast.

SUPPLEMENTARY MATERIAL (CHAPTER 3)

Complementary analysis on brain fractality

Complementing the Hurst exponent and Detrended Fluctuation Analysis (DFA), the fractal dimension of brain signal was further assessed using Higuchi's, Petrosian's, and Sevcik's algorithms, which have previously been used to study EEG brain dynamics (Eslahi et al., 2019; Hadjidimitriou et al., 2010), and are implemented in Neurokit2 python package (Makowski et al., 2021). These methods diverge from Hurst and DFA by focusing on the geometric complexity of the time series. Higuchi's and Petrosian's algorithms estimate the temporal complexity over time, while Sevcik's algorithm measures the signal's curvature length, providing an additional perspective on the fractal characteristics of brain activity.

The findings indicated a significant negative correlation between bFD and stimulus FD in occipital areas, evident in both Petrosian (*effect sizes*: -0.23 to -0.44, *p_{range}*: 0.01 to 1.2e-07) and

Sevcik FD metrics (*effect sizes: -0.28 to -0.34, p_{range}: 8.2e-04 to 2.1e-04*) (refer to **Fig. S1 C-D**). Conversely, Higuchi FD exhibited a different pattern, showing an increase in association with pareidolia for few central sensors (*effect sizes: 0.05 to 0.07, p_{range}: 5.0e-04 to 3.4e-05*), along with a significant interaction between creativity level and pareidolia in the left occipital region (*effect sizes: 0.15 to 0.17, p_{range}: 5.5e-04 to 2.9e-04*) (see **Fig. S1 A-B**). This interaction suggests that for high-creative individuals, a greater number of pareidolic percepts correlates with increased Higuchi FD, whereas for those with lower creativity levels, the effect is reversed.

These findings enhance our primary results obtained using Hurst and DFA. They indicate that, in contrast to measures of long-range temporal correlation, Petrosian and Sevcik FD capture only lower-level processing. This is evidenced by the negative correlation in occipital regions and the absence of interaction with the number of pareidolic percepts. Meanwhile, the Higuchi FD, although not directly related to stimulus FD, uniquely correlates with creativity levels. This suggests that in high-creatives, occipital complexity positively correlates with pareidolia, whereas in low-creatives, the correlation is negative, highlighting distinct effects of pareidolia on visual processing between low and high-creatives.

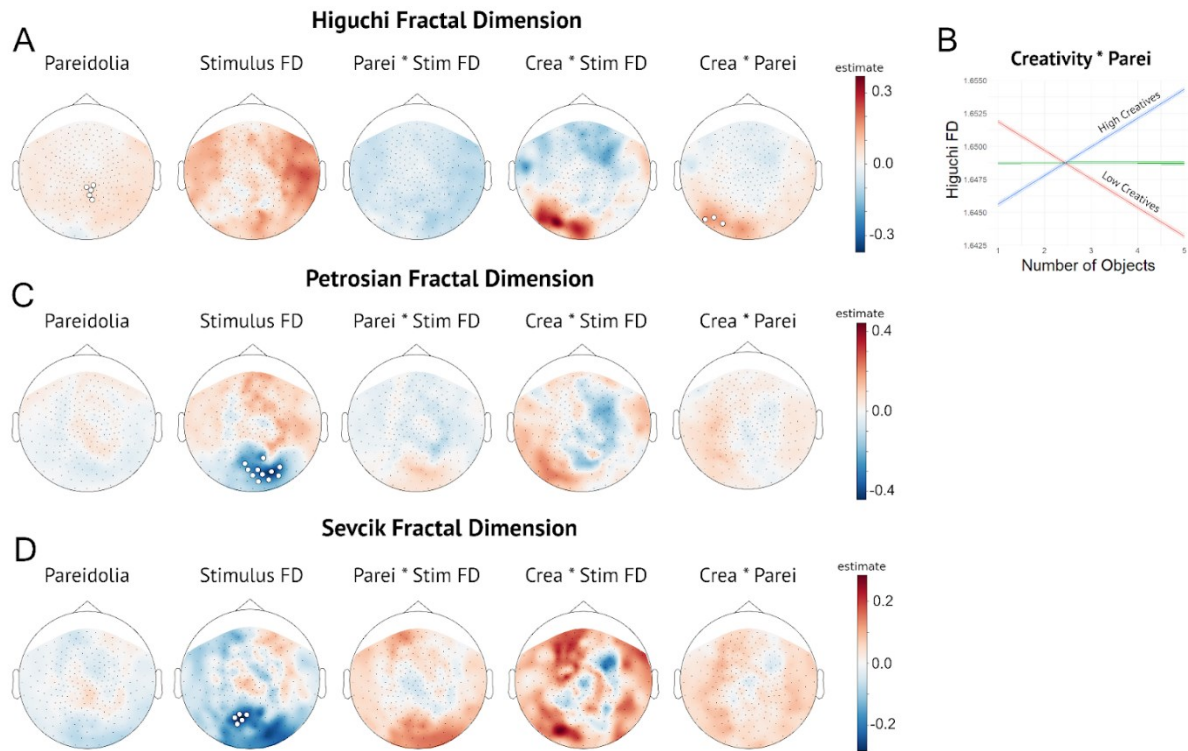


Figure S3.1. Interaction of pareidolia and creativity in predicting fractal dimensions of brain activity. (A) Topographic maps of fixed effects and interaction terms of pareidolia and stimulus FD in predicting Higuchi Fractal Dimension (HFD). (B) Predicted values of the interaction between pareidolia and stimulus FD in predicting HFD, averaged across significant sensors. (C) Topographic maps of fixed effects and interaction terms of pareidolia and stimulus FD in predicting Petrosian Fractal Dimension (PFD). (D) Topographic maps of fixed effects and interaction terms of pareidolia and stimulus FD in predicting Sevcik Fractal Dimension (SFD). White dots across the topographic maps represent statistically significant regions ($p < .05$ after FDR correction). $N_{obs} = 2687$.

| Effect Name | Coefficient Range | P-value Range |
|-------------------------|-------------------|----------------------|
| (Intercept) | (-9.21, 4.24) | (5.79e-15, 1.90e-03) |
| theta | (-10.74, -2.27) | (8.17e-08, 5.07e-04) |
| alpha | (2.43, 10.07) | (1.46e-08, 1.25e-03) |
| low_beta | (-8.43, 5.39) | (6.81e-08, 4.29e-04) |
| high_beta | (-4.34, -1.91) | (4.29e-10, 3.14e-03) |
| gamma1 | (-4.73, -1.89) | (1.26e-06, 4.44e-04) |
| gamma2 | (-6.48, -1.45) | (2.04e-07, 3.21e-04) |
| gamma3 | (-15.7, 1.86) | (1.11e-25, 2.55e-03) |
| LZ | (-2.64, 8.31) | (1.15e-17, 4.41e-03) |
| theta : parei | (1.8, 14.31) | (2.75e-09, 1.27e-03) |
| theta : DAT | (-8.78, 2.87) | (6.05e-07, 5.27e-04) |
| alpha : parei | (-11.69, -2.22) | (9.63e-07, 8.60e-04) |
| alpha : DAT | N/A | N/A |
| low_beta : parei | (-5.82, 10.49) | (1.21e-06, 1.29e-05) |
| low_beta : DAT | (-6.79, -4.18) | (2.29e-06, 6.12e-05) |
| high_beta : parei | (2.06, 5.26) | (4.36e-10, 3.44e-03) |
| high_beta : DAT | N/A | N/A |
| gamma1 : parei | (3.02, 3.34) | (5.89e-06, 7.90e-06) |
| gamma1 : DAT | (-3.59, 1.7) | (2.64e-07, 6.45e-04) |
| gamma2 : parei | (1.9, 7.78) | (1.36e-07, 1.96e-04) |
| gamma2 : DAT | N/A | N/A |
| gamma3 : parei | (1.39, 18.31) | (1.80e-30, 2.53e-03) |
| gamma3 : DAT | (-8.97, -0.76) | (1.43e-18, 7.42e-03) |
| LZ : parei | (-8.56, 3.04) | (7.85e-16, 3.49e-03) |
| LZ : DAT | (-9.71, 5.58) | (2.83e-28, 3.31e-03) |
| theta : parei : DAT | (-3.82, 11.15) | (5.39e-06, 5.41e-04) |
| alpha : parei : DAT | N/A | N/A |
| low_beta : parei : DAT | (3.47, 10.28) | (3.14e-07, 6.31e-04) |
| high_beta : parei : DAT | N/A | N/A |
| gamma1 : parei : DAT | (-3.04, 4.7) | (1.33e-07, 1.06e-03) |
| gamma2 : parei : DAT | N/A | N/A |
| gamma3 : parei : DAT | (1.21, 11.09) | (2.90e-16, 7.58e-03) |
| LZ : parei : DAT | (-7.83, 12.5) | (8.00e-25, 2.78e-03) |

Table S3.1. Coefficient range and *p*-value range for significant electrodes in the model predicting resting state conditions (refer to Fig. 6)

SUPPLEMENTARY MATERIAL (GENERAL DISCUSSION)

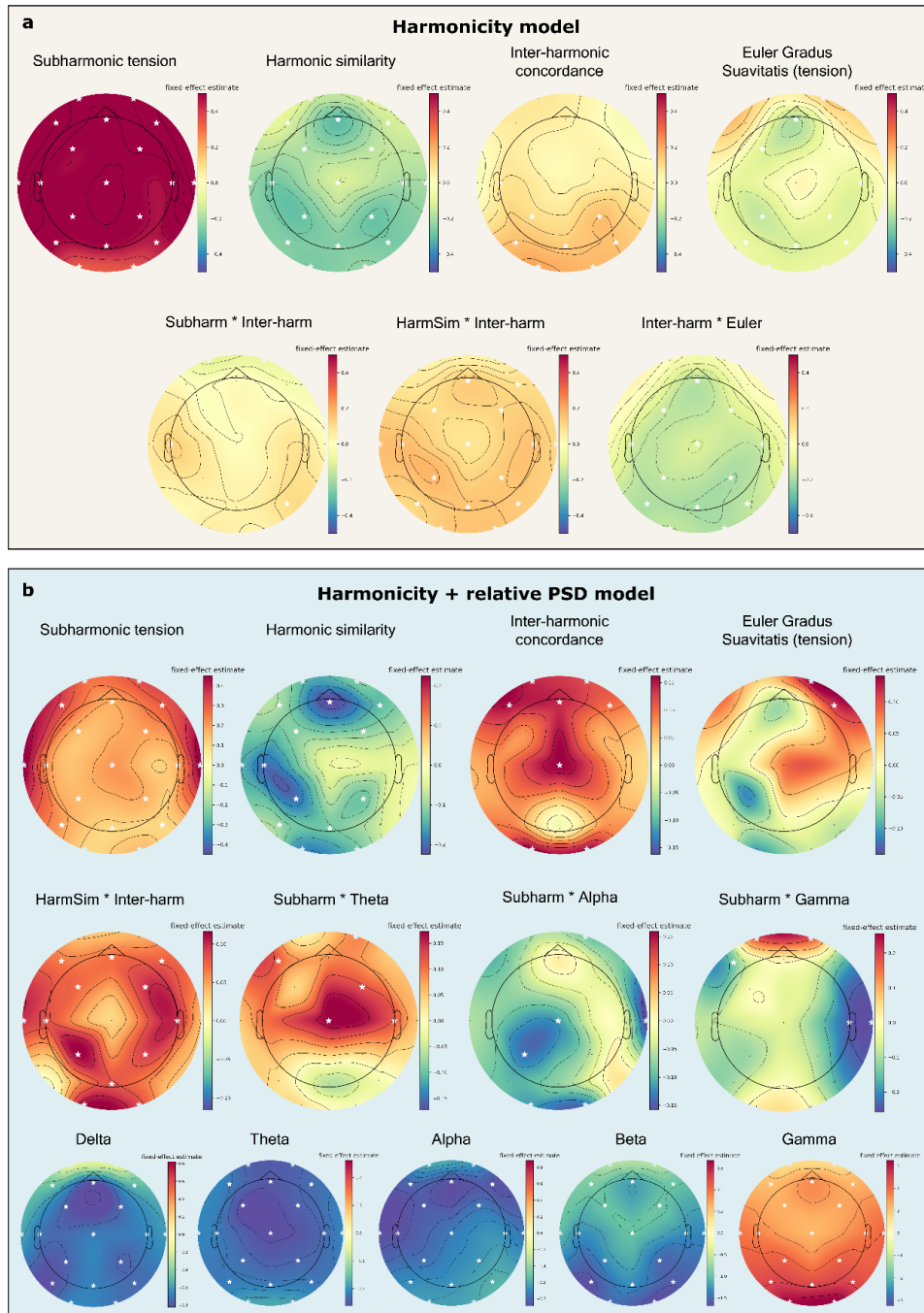


Figure S6.1. Comparing wakefulness with Slow-Wave-Sleep using harmonicity metrics. (a) Topomaps of the estimate of the harmonicity model. This model had four harmonicity metrics, the mean peaks frequency, and all the two-way interactions as fixed effects. White stars indicate significance level at $p < 0.01$. **(b)** Topomaps of the estimate of the harmonicity + relative PSD model. This model is the same as the harmonicity model with the addition of relative Power Spectral Density values as well as their two-way interactions. White stars indicate significant level at $p < .05$. The values for the colorbar are not leveled across topomaps since the values were too different, hence the topography of the effect would not have

been visible. Frequency bands: Delta (2-4Hz), Theta (4-8Hz), Alpha (8-13Hz), Beta (13-30Hz), Gamma (30-60Hz).

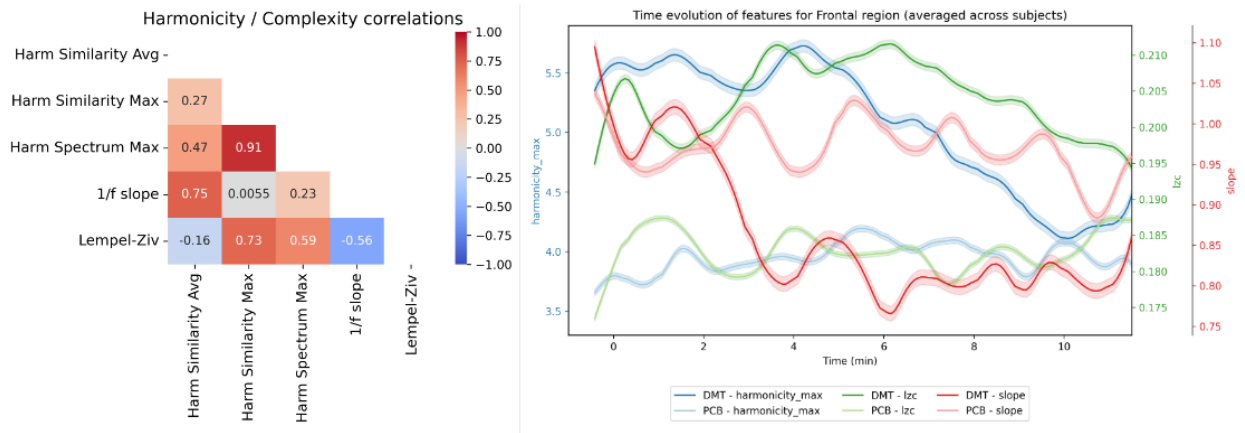


Figure S6.2. Tracking the temporal evolution of DMT using harmonicity and complexity metrics. **Left:** This part of the figure displays a correlation matrix that elucidates the relationship between various measures of harmonicity and complexity. Each cell within the matrix indicates the strength and direction of the correlation between two measures, with the color intensity and sign indicating the magnitude and nature (positive/negative) of the correlation coefficient. **Right:** This graph illustrates the temporal evolution of features for the frontal region, averaged across subjects, comparing the effects of DMT and Placebo. It shows the variation over time (in minutes) of the maximum harmonicity, Lempel-Ziv complexity (LzC), and 1/f slope, providing insight into how these measures change in response to the substances. The data is derived from the study conducted by Timmermann et al. (2019).

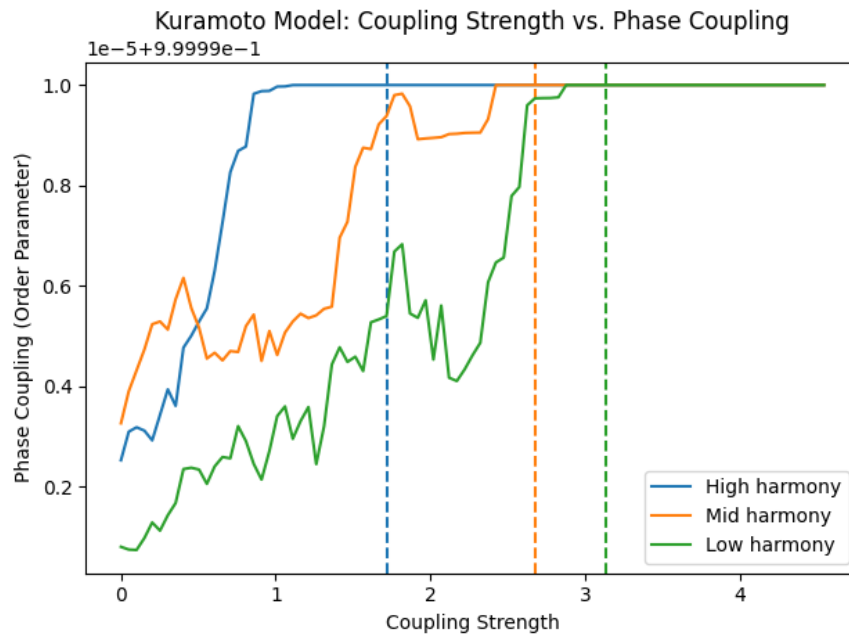


Figure S6.3. Impact of harmonicity on phase-coupling using Kuramoto Model. Three Kuramoto models were compared, each with different values of harmonicity between their coupled oscillators.